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The new GLA Economics forecast models for London's economy

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Contents

Abstract

GLA Economics produces medium-term forecasts for Greater London's economy twice a year. Since December 2019, these forecasts rely on a new econometric methodology - i.e., VAR modelling - which has substantially improved the accuracy and robustness of the mentioned economic predictions. This working paper presents the new GLA Economics forecast models and evaluates their performance with respect to the previous methodology, a comparable independent forecaster, and outturn data[1].

[1] A non-technical summary of this working paper will be provided in the next GLA Economics - London Economic Outlook release in Spring 2020.

1 Introduction

Since 2003, GLA Economics (GLAE, henceforth) has published economic forecasts for the UK region of Greater London (London, hereafter) twice a year[2]. In particular, GLAE estimates the following variables in both levels and annualised growth rates on a quarterly basis[3]: real Gross Value Added (GVA), real GVA by industry, workforce jobs, workforce jobs by industry, household income, and household expenditure. The forecasting horizon for these variables is the medium-term, understood as the year of the forecasts publication date and the two following years.

GLAE's medium-term forecasts play a central role in supporting policymaking at the Greater London Authority (GLA). Forecasts are used as a basis for key medium-term policies and planning measures set by the Mayor of London and the London Assembly such as the London Plan, the long-term employment projections for London, and the London Industrial Strategy, among other initiatives. Besides this, national and international economic agents benefit from forecasts of an economy which represents 23.7% of UK's total output and it is worth £436.5 billion[4].

Due to its importance, GLAE is committed to improving the accuracy and robustness of its London's economy forecasts when possible. This working paper presents a recent update of the GLAE forecasting methodology which has achieved both aims. In particular, the revision consists in the incorporation of the following elements into the forecasting process: 1) new model specifications based on VAR modelling, 2) new econometric techniques, 3) new data sources, 4) omitted relevant variables, and 5) additional robustness checks. As a main result, the new models improved forecasting accuracy between 66% and 71% - on average – for London's Real GVA and London's workforce jobs when compared to the old GLAE models. This improvement reached between 53% and 61% for forecasts of household real income and household real expenditure in London. By industries, results are more volatile but the smallest average improvement is 37%. The new models were first applied to GLAE forecasts published in 'London's Economic Outlook – Autumn 2019'.

Putting this revision into perspective, the new methodology can be considered as a structural change with respect to the previous forecasting process. GLAE started producing its own modelling of the London's economy in year 2015 and the initial methodology had continued since then. Previously, from 2007, GLAE forecasts were produced using an econometric model created by the economic consultancy Volterra Partners-UK while, between 2003 and 2006, these forecasts were directly provided by the economic consultancy Experian-UK.

The remainder of this study is structured as follows. In the next section, a literature review on regional economic forecasting is provided. In the third section, the new GLAE forecasting methodology is described for each variable of interest. This is followed by a fourth section explaining the data employed in this work. The performance analysis of the new forecasts is shown in the fifth section. Finally, the paper presents its conclusions and limitations.

[2] See GLA's 'London's Economic Outlook' report (LEO) in its spring and autumn versions.
[3] Note that LEO publications generally show annual forecasts only but these derive from quarterly estimates.
[4] Based on data from: Office for National Statistics (ONS) – Regional Accounts. Data refers to year 2018.

2 Background to regional economic forecasting

The production of economic forecasts at the regional level has been traditionally undeveloped and mostly elaborated under confidentiality by a reduced number of local authorities in advanced economies. Besides, academic literature in this field remains scarce when compared to country-level studies.

Three main factors might explain the historically limited evidence of sub-national economic forecasts. First, there is no high demand for regional forecasts yet. Public administrations and international organizations have usually focused on national aggregates to develop policy support tools such as econometric models for forecasting, especially in non-federal countries. Similarly, the number of private companies producing regional forecasts on a commercial basis remains very low and concentrated in a few developed countries. Second, the information base upon which regional econometric models are constructed is much more limited than that of their national counterparts. For example, official output estimates - which are normally built around the components of aggregate demand at the national level - generally switch to the supply-side approach at the regional level - i.e., gross value added (GVA) - because quality data on variables such as inflation, investment, consumption, and net exports (including interregional trade) are often unavailable at regional level. And third, even when regional economic time series become accessible, they are generally with an annual frequency only, have limited historic data, and are released with a long delay. Furthermore, noisy dynamics and outliers are more frequent in regional data than for national data. As a result, all these issues importantly reduce both the econometric modelling options and the performance of forecasts at regional level (Bell, 2006).

Given these limitations, macroeconomic variables such as employment, household income, and household expenditure have been essentially ignored in the literature of regional forecasting. However, for regional output there exists international evidence exploring several methodologies with a predominant aim: building historic quarterly series – consistent with official annual estimates if available - to produce short-term and very-short-term forecasts (i.e., from current period to one year ahead).

In this direction, the most common approach remains the creation and projection of a synthetic activity index (also known as 'composite output index') as a proxy of regional output on a quarterly basis (Artola et al., 2018). This method combines available higher frequency (monthly and quarterly) indicators such as PMIs, registration of vehicles, retail sales, and employment data to obtain one single quarterly measure of economic activity, the 'index'. This index may be then linearly projected to the future for a reduced number of periods. The technique is relatively straightforward to construct and has the advantage of incorporating available up to date information, but its simplicity also penalises forecasting accuracy (Stock, 2005). Looking at more complex econometric techniques, Henzel et al. (2016) forecasted GDP growth in the German region of Saxony by feeding regional, national, and international information into a Bridge Equations model, a popular short-term forecasting method for obtaining quarterly estimates from monthly data. Wang et al. (2014) projected quarterly GDP growth rates one year ahead for Chinese regions by using MIDAS regressions, a flexible econometric specification when several data frequencies are involved but is again not applicable to longer-term forecasting. Another tool that has been recently proven to be successful in tracking output growth is factorial analysis. This technique is typically used to extract common dynamics from a set of recent activity indicators and then use that information to predict a target variable (GDP or GVA) in the very-short-term (also known as 'nowcasting'). Good examples of this approach are Bok et al. (2017) who produced nowcasts of GDP growth for U.S. states[5] and Chernis et al. (2017) who applied the same methodology for Canadian provincial GDP. Also, within factorial analysis, probably the most relevant

[5] The US Bureau of Economic Analysis (BEA) regularly publishes quarterly GDP estimates for all US States since year 2005. However, no evidence of medium-term forecasts was found in the literature using these data.

work so far involving nowcasting of regional GDP was recently published by Gil et al. (2019) for Spanish regions. These authors overcome some of the undesired features of regional modelling such as the lack of historic quarterly series and annual estimates being released with long delay by introducing Bayesian methods[6] into a dynamic factor model.

With regards to the UK, Grant et al. (2015) opted for a MIDAS model to nowcast real GDP growth in Scotland but a more recent and thorough work for all UK regions is the paper by Koop et al. (2018). In particular, these authors successfully predict up to date GVA growth rates - both in real and nominal terms – since 1970 on a quarterly basis[7]. Until September 2019, a major limitation when forecasting UK regional output - especially on a quarterly basis - was that official GVA figures released by the ONS were published with a year delay and at annual frequency only. Koop et al. (2018) overcome these issues by developing a mixed-frequency Vector Autoregressive (VAR) model. VAR modelling is a popular forecasting method which consists in a multi-equation system where endogenous variables depend – for a given time point - on its past but also on the past of other endogenous variables within the model[8]. Authors also choose a 'top-down' approach which implies that regional estimates are constrained by imposed national aggregates with no possibility for the regional variables to feed back to the national model or influence its outcomes.

Even more interestingly for the purposes of this study, in addition to GLAE forecasts, the economic consultancy Experian-UK (Experian, hereafter) currently estimates real GVA, workforce jobs, household real income, and household real expenditure quarterly series for London in the medium-term. As opposed to GLAE, this company makes use of a general equilibrium (GE) model for each UK region/nation and follows a 'top-down' approach as in Koop et al. (2018). GE models are structural models which attempt to explain the behaviour of supply, demand, and prices in a whole economy by modelling its main economic agents and interactions. They can be developed in relatively simple forms as in Devarajan et al. (1997) or represent more complex interactions as in Dynamic Stochastic GE models (DSGE) (see Galí, 2008). Experian-UK makes use of a customised version of a DSGE model for the UK that was originally created by the National Institute of Social & Economic Research's (NIESR) and it is called 'NiGEM' [9].

Given the characteristics of GLAE forecasts (i.e., medium-term horizon on a quarterly frequency), the new GLAE modelling of London's real GVA feeds from the above-mentioned references but does not try to replicate any of those because of the following considerations. First, in September 2019, the ONS published new historic quarterly real GDP estimates for UK regions/nations which are being released with only a two-quarter delay over the reference period. This important improvement in terms of availability of London historic data implies that it is no longer essential to depend on mixed-frequency methodologies to produce quarterly forecasts of London's output. Second, the fact that GLAE forecasts focus on the medium-term (two to three years ahead) makes short-term and nowcasting techniques suboptimal and invalid, respectively, in this framework (Carriero et al., 2019). Third, GLAE only produces forecasts for the London's economy. This means that using a 'top-down' approach in the GLAE forecasting process would unnecessarily constrain London forecasts by UK forecasts produced ex-ante while GLAE is not interested in producing estimates for other UK regions/nations either[10]. Therefore, this approach has been discarded for the GLAE forecasting process as well. Finally, GE models are widely accepted as good representations of the economy and its interlinkages but frequently underperform in terms of forecasting when compared to VAR

[6] In particular, authors make use Monte Carlo-Markov chains based on hundreds of repetitions to simulate the density functions of the parameters in the econometric model. When this method is combined with a prior information factor can produce unbiased and robust estimates of the dependent variable, especially in linear models (Gil et al., 2019).
[7] Each GVA growth rate estimate shows the average of the last four quarters in a quarterly frequency. These quarterly estimates are consistent with the official ONS annual observations.
[8] Koop et al. (2018) also introduce a machine learning method based on the hierarchical Dirichlet-Laplace prior 'to ensure optimal shrinkage and parsimony in the VAR model'. For more detail, see Koop et al. (2018).
[9] For more detail on the Experian model see here.
[10] Although UK estimates produced by external sources have been incorporated into the GLAE modelling when added predictive power.

modelling, especially for small-sized models and long-term horizons (Carriero et al., 2019). This last statement will be verified for the case of London in the fifth section of this document by comparing the performance of independent comparable forecasts resulting from a GE model against the performance of the new GLAE estimates.

In this context, four forms of VAR econometric modelling – (un)restricted, Bayesian VAR (BVAR), and Vector Error Correction (VECM) - have been considered as the most appropriate candidates to produce medium-term forecasts of London's real GVA on a quarterly basis. The same VAR techniques have been studied to produce forecasts of real GVA by industry, workforce jobs, workforce jobs by industry, household real income, and household real expenditure in London as well. The selected options prove to be versatile and reliable tools for GLAE forecasts and, furthermore, complement a long list of medium-term macroeconomic forecasting works at the country level (see D'Agostino et al., 2013; Caraiani, 2018; Bäurle et al., 2018, and Chauvet et al., 2012; among many others). Where VAR modelling was found not applicable or underperforming for GLAE purposes - i.e., only for the case of household real income -, classic multiple linear regression models resulted in a successful alternative.

The concrete data and final methodologies employed for each variable of interest are explained in detail in the next two sections.

3 The new GLAE forecast models for London's economy

This section describes the methodology - including the econometric specifications – applied to the new GLAE forecasts for real GVA, real GVA by industry, workforce jobs, workforce jobs by industry, household real income, and household real expenditure in London. Due to the large number of different models involved, each variable of interest will have a sub-section in this chapter. Data and sample information is provided jointly in the next section of this paper.

3.1 The real GVA headline model

By extension of the VAR model proposed by Sdrakas (2003), London's real GVA is forecasted through a third-order Unrestricted VARX (UVARX) with three endogenous variables – the suffix 'X' in 'VARX' only indicates that the VAR contains exogenous variables as well -. This means that London's real GVA, at any given quarter, is set to depend on itself - lagged up to three periods - but also on the past of two other endogenous variables which are the UK's real GVA and London's workforce jobs. Besides, London's real GVA depends on four other relevant variables which have been introduced as exogenous. Consequently, the empirical model in growth rates can be written in its reduced form as:

$$\begin{aligned}
\Delta ln(lon_gva)_t &= c_1 + \theta_{1,1}\Delta ln(lon_gva)_{t-1} + \theta_{1,2}\Delta ln(lon_gva)_{t-2} + \theta_{1,3}\Delta ln(lon_gva)_{t-3} + \\
&+ \theta_{1,4}\Delta ln(uk_gva)_{t-1} + \theta_{1,5}\Delta ln(uk_gva)_{t-2} + \theta_{1,6}\Delta ln(uk_gva)_{t-3} + \theta_{1,7}\Delta ln(lon_wfj)_{t-1} + \\
&+ \theta_{1,8}\Delta ln(lon_wfj)_{t-2} + \theta_{1,9}\Delta ln(lon_wfj)_{t-3} + \theta_{1,10}\Delta ln(lon_hhspe)_t + \theta_{1,11}\Delta ln(lon_prod)_t + \\
&+ \theta_{1,12}lon_pmi_{t-2} + \theta_{1,13}\Delta ln(uk_binv)_t + \varepsilon_{1,t} \\
\Delta ln(uk_gva)_t &= c_2 + \theta_{2,1}\Delta ln(lon_gva)_{t-1} + \theta_{2,2}\Delta ln(lon_gva)_{t-2} + \theta_{2,3}\Delta ln(lon_gva)_{t-3} + \\
&+ \theta_{2,4}\Delta ln(uk_gva)_{t-1} + \theta_{2,5}\Delta ln(uk_gva)_{t-2} + \theta_{2,6}\Delta ln(uk_gva)_{t-3} + \theta_{2,7}\Delta ln(lon_wfj)_{t-1} + \\
&+ \theta_{2,8}\Delta ln(lon_wfj)_{t-2} + \theta_{2,9}\Delta ln(lon_wfj)_{t-3} + \theta_{2,10}\Delta ln(lon_hhspe)_t + \theta_{2,11}\Delta ln(lon_prod)_t + \\
&+ \theta_{2,12}lon_pmi_{t-2} + \theta_{2,13}\Delta ln(uk_binv)_t + \varepsilon_{2,t} \\
\Delta ln(lon_wfj)_t &= c_3 + \theta_{3,1}\Delta ln(lon_gva)_{t-1} + \theta_{3,2}\Delta ln(lon_gva)_{t-2} + \theta_{3,3}\Delta ln(lon_gva)_{t-3} + \\
&+ \theta_{3,4}\Delta ln(uk_gva)_{t-1} + \theta_{3,5}\Delta ln(uk_gva)_{t-2} + \theta_{3,6}\Delta ln(uk_gva)_{t-3} + \theta_{3,7}\Delta ln(lon_wfj)_{t-1} + \\
&+ \theta_{3,8}\Delta ln(lon_wfj)_{t-2} + \theta_{3,9}\Delta ln(lon_wfj)_{t-3} + \theta_{3,10}\Delta ln(lon_hhspe)_t + \theta_{3,11}\Delta ln(lon_prod)_t + \\
&+ \theta_{3,12}lon_pmi_{t-2} + \theta_{3,13}\Delta ln(uk_binv)_t + \varepsilon_{3,t} \qquad (1)
\end{aligned}$$

where $\Delta ln(variable)_t$ is the quarter-on-the-same-quarter-previous-year growth rate (also known as annualised growth rate) of the corresponding variable at quarter *t*. With regards to the three endogenous variables, *lon_gva* is London's real GVA – the variable of interest in this model -, *uk_gva* is UK's real GVA, and *lon_wfj* is the number of workforce jobs in London. In addition to the endogenous variables, this VAR contains the following four regressors assumed as exogenous: *lon_hhspe* is household real consumption expenditure in London, *lon_prod* is London's labour productivity, *lon_pmi* is London's Purchasing Managers Index (PMI) for new business, and *uk_binv* equals UK business investment. ε is the error term. More detail on each of these variables and its sources – not only for Specification (1) but also for all forecast models - is provided in Table 1 within section 4 of this paper. Other potentially relevant variables such as 'London's net exports', 'London's economic activity rate index' or 'London's PMI for business activity' have been tested and discarded due to lack of predictive power.

All the above-mentioned variables are integrated of order one - I(1) - in levels according to the Augmented-Dickey Fuller (ADF) test, which indicates that they are stationary when transformed to annualised growth rates as shown in the model. The only exception to this is *lon_pmi* which is already a stationary variable in levels. Stationarity of time series means that their statistical properties (or the process generating them) do not change over time which is a necessary condition for the use of VAR modelling. This condition is satisfied for all the variables used in this study although not shown in the next sub-sections of this chapter to avoid repetition.

Specification (1) is an 'unrestricted' model as no restrictions on the regressors have been applied, i.e., all equations in their right-hand side are equal. UVARX modelling requires OLS estimation of the parameters which means that estimated θ values are the result of minimizing the sum of the squares in the difference between observed and predicted values of the dependent variable. Optimal lag length (third order) in the model is based on the Akaike criteria while optimal lag length for the exogenous variables is based on a *t-test* for significance. Additionally, the model has been successfully tested to prove that its residuals present no autocorrelation (LM Test), are normally distributed (Cholesky Method), and are homoscedastic (White Test).

In search of the optimum model selection, other forms of VAR modelling than Specification (1) were tested to forecast London's real GVA. However, all those options resulted in a worse performance in terms of forecasting accuracy[11] when compared to the model presented above. These models are: 1) Specification (1) without $\Delta ln(lon\_wfj)_t$ as endogenous variable, that is, an UVARX(3) with two endogenous variables; 2) Specification (1) with imposed restrictions on some exogenous variables, i.e., a Restricted VARX(3) with three endogenous variables[12]; and 3) a Bayesian VAR(3)[13] with the same equations as in Specification (1). Vector Error Correction models[14] were finally not considered here due to absence of a cointegrating relationship between both *lon_gva* and *uk_gva*, and *lon_gva* and *lon_wfj*[15] as it can be observed in Table A1 of the Annex.

3.2 The real GVA by industry models

Following a similar approach to the real GVA headline model, forecasts of real GVA growth rates broken down by London economic sectors are modelled through an Unrestricted VARX model with three endogenous variables. In concrete, London's annualised growth in real output generated by each industry can be determined by the past performance of that industry but also on past UK's real GVA growth rates and past London's workforce jobs growth rates for the same industry. Only one exogenous variable (labour productivity by industry in London) was found relevant in this model. The reduced form of the real GVA by industry model can be expressed as follows:

$$\Delta ln(lon\_gva)_{i,t} = c_{1,i} + \theta_{1,1,i}\Delta ln(lon\_gva)_{i,t-z} + \theta_{1,2,i}\Delta ln(uk\_gva)_{i,t-z} + \theta_{1,3,i}\Delta ln(lon\_wfj)_{i,t-z} + \\ + \theta_{1,4,i}\Delta ln(lon\_prod)_{i,t} + \varepsilon_{1,i,t}$$

$$\Delta ln(uk\_gva)_{i,t} = c_{2,i} + \theta_{2,1,i}\Delta ln(lon\_gva)_{i,t-z} + \theta_{2,2,i}\Delta ln(uk\_gva)_{i,t-z} + \theta_{2,3,i}\Delta ln(lon\_wfj)_{i,t-z} + \\ + \theta_{2,4,i}\Delta ln(lon\_prod)_{i,t} + \varepsilon_{2,i,t}$$

$$\Delta ln(lon\_wfj)_{i,t} = c_{3,i} + \theta_{3,1,i}\Delta ln(lon\_gva)_{i,t-z} + \theta_{3,2,i}\Delta ln(uk\_gva)_{i,t-z} + \theta_{3,3,i}\Delta ln(lon\_wfj)_{i,t-z} + \\ + \theta_{3,4,i}\Delta ln(lon\_prod)_{i,t} + \varepsilon_{3,i,t} \qquad (2)$$

[11] This was evaluated for both point and density forecasts for several in-sample periods.
[12] Restricted VAR modelling requires Maximum Likelihood estimation of the parameters rather than OLS methodology.
[13] Bayesian VAR models involve a Generalised Least Squares methodology as the estimation of the parameters is not only based on the available data but also on 'prior information'. For more detail on this methodology see Herbst and Schorftheide (2012) and Smets and Wouters (2007).
[14] Error Correction models (known as VECM in its vectoral form) are popular specifications for estimating short-term and long-term effects of one time series on another. The term 'error-correction' relates to the fact that deviations from the long-run equilibrium (errors) influence short-run dynamics. This model allows to directly estimate the speed at which the dependent variable returns to its long-run equilibrium after a change in other variables. Therefore, the use of VEC models is a valid alternative to medium-term forecasting. For more detail on VECM forecasting of national GDP see Jenkin (2014).
[15] This fact indicates that despite a high correlation and even a causal effect of these I(1) variables on each other, differences in their averages are not constant over the long-term. In other words, there is no stationary relationship between those I(1) variables in the long-term, which is a necessary condition for the use of VEC models. This phenomenon must not be confused with the individual stationarity of the variables or with a 'spurious relationship' which is simply a statistical relationship between two variables where an apparent (but not actual) causal effect takes place.

where $\Delta ln(variable)_t$ is the annualised growth rate of the corresponding variable at quarter t. The subindex i indicates 'industry'. A total of twenty groups of economic activities have been considered in this paper for both London and UK variables - the list of industries is shown in Table 2 -. Hence, Specification (2) is estimated twenty times to produce forecasts for all industries. $(lon\_gva)_i$ is the variable of interest in Specification (2) which is London's real GVA by industry, $(uk\_gva)_i$ is UK's real GVA by industry, and $(lon\_wfj)_i$ stands for the number of workforce jobs by London sector. $(lon\_prod)_i$ is London's labour productivity by industry and it has been assumed as exogenous in this model. z is the order of the UVARX which varies from one to four depending on the industry, based on the Akaike criteria. Optimal lag length for the exogenous variable is based on a *t-test* for significance[16]. ε is the error term. No other available relevant variables were found to improve the forecasting performance of Specification (2).

As in Specification (1), tests for the validity of the residuals were successfully conducted. This step will be assumed for the remaining models in this section. Additionally, sectoral estimates produced by Specification (2) are adjusted ex-post to equal aggregate real GVA resulting from Specification (1) forecasts[17].

The following models were found valid second best options for forecasting London's real GVA by industry but finally rejected in favour of Specification (2) based on its relative performance: 1) Specification (2) but getting rid of $\Delta ln(lon\_prod)_{i,t}$, i.e., an UVARX($z$) with three endogenous variables and no exogenous variables; 2) a Multiple Linear Regression model with $\Delta ln(lon\_gva)_{i,t}$ as dependent variable and $\Delta ln(uk\_gva)_{i,t}$ and $\Delta ln(lon\_wfj)_{i,t}$ as regressors - note that this model requires the strong assumption of independent variables being exogenous -; and 3) a Random Walk model (in levels)[18].

3.3 The workforce jobs headline model

The selected approach for forecasting quarterly annualised growth rates of the number of workforce jobs in London differ to some extent but not substantially from Specification (1). In this case, the dependent variable of interest can be essentially explained by lagged values of itself and by past London's real GVA growth rates. Besides, London's labour productivity and UK business investment have an effect in this model as exogenous variables. Consequently, Specification (3) can be written as an Unrestricted VARX model with two endogenous variables and two exogenous variables. The optimal lag length in this model is two (second-order UVARX):

$$\Delta ln(lon\_wfj)_t = c_1 + \theta_{1,1}\Delta ln(lon\_wfj)_{t-1} + \theta_{1,2}\Delta ln(lon\_wfj)_{t-2} + \theta_{1,3}\Delta ln(lon\_gva)_{t-1} + \\ + \theta_{1,4}\Delta ln(lon\_gva)_{t-2} + \theta_{1,5}\Delta ln(lon\_prod)_t + \theta_{1,6}\Delta ln(uk\_binv)_t + \varepsilon_{1,t}$$

$$\Delta ln(lon\_gva)_t = c_2 + \theta_{2,1}\Delta ln(lon\_wfj)_{t-1} + \theta_{2,2}\Delta ln(lon\_wfj)_{t-2} + \theta_{2,3}\Delta ln(lon\_gva)_{t-1} + \\ + \theta_{2,4}\Delta ln(lon\_gva)_{t-2} + \theta_{2,5}\Delta ln(lon\_prod)_t + \theta_{2,6}\Delta ln(uk\_binv)_t + \varepsilon_{2,t} \qquad (3)$$

where $\Delta ln(variable)_t$ is the annualised growth rate of any variable at quarter t, *lon_wfj* is the number of workforce jobs in London – the variable of interest in this model -, *lon_gva* is London's real GVA, *lon_prod* is London's labour productivity, and *uk_binv* equals UK business investment. ε is the error term. Other potentially relevant variables such as 'London's population', 'UK's number of workforce jobs' or 'London's PMI for employment' have been finally removed due to lack of predictive power.

The following three valid alternatives to Specification (3) were tested but finally not chosen for the forecast of London's workforce jobs as a result of their worse relative performance: 1) A Multiple Linear Regression

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[16] As in Specification (1) and Specification (2), Akaike criteria and *t-test* for significance have been used for the optimal lag selection in the remaining models of this paper.
[17] More detail on this method can be found in Keijonen and Lohuizen (2016).
[18] See Kirikos (2000) for an application of this classic and simple forecast model which essentially predicts that the value of a random variable in t equals the value of the same variable in t-1 plus an error.

model with $\Delta ln(lon\_wfj)_t$ as dependent variable and $\Delta ln(lon\_gva)_t$ and $\Delta ln(lon\_prod)_t$ as regressors - note that this model requires independent variables being exogenous[19]-; 2) a Bayesian VAR(2) with the same equations as in Specification (3); and 3) all models described in this subsection but with variables expressed in levels rather than growth rates. Vector Error Correction models were finally not considered here because no cointegrating relationship was found between *lon_gva* and *lon_wfj* as already commented for Specification (1) (see Table A1 of the Annex).

3.4 The workforce jobs by industry models

In line with Specification (3), forecasts of workforce jobs by London economic sector are modelled through an Unrestricted VARX model with two endogenous variables. The main difference between the models by industry and Specification (3) is that the first ones only use one exogenous variable rather than two as in the headline model. Having pointed this out, the annual growth rate of workforce jobs in London for a given industry is affected at quarter *t* by the past of this time series, by the past growth of London's real GVA of the same industry and by the current labour productivity growth for the respective industry. The reduced form of this UVARX for workforce jobs by industry in London is shown through Specification (4):

$$\Delta ln(lon\_wfj)_{i,t} = c_{1,i} + \theta_{1,1,i}\Delta ln(lon\_wfj)_{i,t-z} + \theta_{1,2,i}\Delta ln(lon\_gva)_{i,t-z} + \theta_{1,3,i}\Delta ln(lon\_prod)_{i,t} + \varepsilon_{1,i,t}$$

$$\Delta ln(lon\_gva)_{i,t} = c_{2,i} + \theta_{2,1,i}\Delta ln(lon\_wfj)_{i,t-z} + \theta_{2,2,i}\Delta ln(lon\_gva)_{i,t-z} + \theta_{2,3,i}\Delta ln(lon\_prod)_{i,t} + \varepsilon_{2,i,t} \qquad (4)$$

where $\Delta ln(variable)_t$ is the annualised growth rate of the corresponding variable at quarter *t*. The subindex *i* indicates 'industry' and the sectoral approach described in subsection 3.2 has been replicated for Specification (4) – go to Table 2 to check the list of twenty industries employed in this work –. $(lon\_wfj)_i$ is the variable of interest in Specification (4) - the number of London's workforce jobs by industry -, $(lon\_gva)_i$ is London's real GVA by industry, and $(lon\_prod)_i$ stands for London's labour productivity by industry which has been assumed as exogenous in these equations. Equally to Specification (2), *z* is the optimal UVARX order which varies from one to four depending on the industry. ε is the error term. No other available relevant variables were found to improve the forecasting performance of Specification (4).

As done for the real GVA by industry models, forecasts derived from Specification (4) are adjusted ex-post to equal aggregate workforce jobs in London resulting from Specification (3)[13].

Some alternative models can be used to replace Specification (4) although at cost of a lower forecasting accuracy: 1) Specification (4) without the variable $\Delta ln(lon\_prod)_{i,t}$, i.e., an UVARX(*z*) with two endogenous variables and no exogenous variables; 2) a Simple Linear Regression model with $\Delta ln(lon\_wfj)_{i,t}$ as dependent variable and $\Delta ln(lon\_gva)_{i,t}$ as unique independent variable[20]; and 3) a Random Walk model (in levels).

3.5 The household real income model

The modelling for the forecasting of household real income in London differs with respect to the previous four specifications. In this case, the selected final model is a classic Multiple Linear Regression model, a simpler econometric tool than VAR modelling although it incorporates an OLS estimation of the parameters as well. The justification for the use of this model simply responds to its clear better performance when it comes to the forecasting of the variable of interest if compared to any other tested specification. Thus, the annualised growth rate of real income in London household can be determined by the annualised growth rate of real income in UK household and by the annualised growth rate of London's real GVA lagged three quarters as Specification (5) illustrates:

$$\Delta ln(lon\_hhinc)_t = c + \theta_1\Delta ln(uk\_hhinc)_t + \theta_2\Delta ln(lon\_gva^*)_{t-3} + \varepsilon_t \qquad (5)$$

[19] Collinearity issues (endogeneity) may arise otherwise. Endogeneity basically depends on the construction of the *lon_prod* series here.
[20] Due to the nature of the data, $\Delta ln(lon\_prod)_{i,t}$ cannot be added as a regressor in this equation without generating a collinearity problem.

where $\Delta ln(variable)_t$ is the annualised growth rate of the variable at quarter *t*, *lon_hhinc* is real income in London household – the dependent variable in this model -, uk_*hhinc* is real income in UK households – which has been assumed as exogenous here in order to provide validity to this model -, *lon_gva** is London's real GVA estimated by Specification (1), and ε is the error term. The individual significance of these regressors can be checked in Table A2 of the Annex[21]. Potentially relevant variables such as 'London's workforce jobs', 'London's employment rate', or 'gross weekly earnings by employees in London' were discovered either not significant in Specification (5) or did not improve forecasting accuracy in other specifications. Therefore, these potential regressors were finally excluded from the modelling of London household real income.

A comprehensive analysis of potential VAR and VECM specifications concluded that these options do not seem appropriate - owing to its weak performance and robustness - for the forecast of household real income in London. Therefore, only Specification (5) but excluding $\Delta ln(lon\_gva^*)_{t-3}$ as independent variable could be thought as a valid modelling alternative. Note that the strong assumption that *uk_hhinc* would be an exogenous variable in that equation must persist as it does in Specification (5).

3.6 The household real expenditure model

The forecast of real expenditure in London household allows VAR modelling. In particular, the selected model is a second-order UVAR with three endogenous variables and no exogenous regressors. In this model, the growth in household real expenditure in London at any given quarter is determined by its lags but also by lagged quarters of household real income growth in London and real GVA growth in London. Formally, the model can be written in its reduced form as:

$$\Delta ln(lon\_hhspe)_t = c_1 + \theta_{1,1}\Delta ln(lon\_hhspe)_{t-1} + \theta_{1,2}\Delta ln(lon\_hhspe)_{t-2} + \theta_{1,3}\Delta ln(lon\_hhinc)_{t-1} + \\ + \theta_{1,4}\Delta ln(lon\_hhinc)_{t-2} + \theta_{1,5}\Delta ln(lon\_gva)_{t-1} + \theta_{1,6}\Delta ln(lon\_gva)_{t-2} + \varepsilon_{1,t}$$

$$\Delta ln(lon\_hhinc)_t = c_2 + \theta_{2,1}\Delta ln(lon\_hhspe)_{t-1} + \theta_{2,2}\Delta ln(lon\_hhspe)_{t-2} + \theta_{2,3}\Delta ln(lon\_hhinc)_{t-1} + \\ + \theta_{2,4}\Delta ln(lon\_hhinc)_{t-2} + \theta_{2,5}\Delta ln(lon\_gva)_{t-1} + \theta_{2,6}\Delta ln(lon\_gva)_{t-2} + \varepsilon_{2,t}$$

$$\Delta ln(lon\_gva)_t = c_3 + \theta_{3,1}\Delta ln(lon\_hhspe)_{t-1} + \theta_{3,2}\Delta ln(lon\_hhspe)_{t-2} + \theta_{3,3}\Delta ln(lon\_hhinc)_{t-1} + \\ + \theta_{3,4}\Delta ln(lon\_hhinc)_{t-2} + \theta_{3,5}\Delta ln(lon\_gva)_{t-1} + \theta_{3,6}\Delta ln(lon\_gva)_{t-2} + \varepsilon_{3,t} \quad (6)$$

where $\Delta ln(variable)_t$ is the annualised growth rate of any variable at quarter *t*, *lon_hhspe* is real expenditure in London household – the variable of interest in this model –, *lon_hhinc* is real income in London household – note that this variable is estimated independently from Specification (5) as *lon_hhinc* works as an endogenous variable in Specification (6) –, *lon_gva* is London's real GVA, and ε is the error term. 'Consumer confidence in London' was finally rejected as a relevant variable in Specification (6) due to its lack of predictive power.

Two second-best modelling alternatives to Specification (6) are: 1) A second-order Vector Error Correction model[22] with *lon_hhspe* and *lon_hhinc* as endogenous variables since *lon_hhspe* was found to be cointegrated with *lon_hhinc* (see Table A1 of the Annex); and 2) a Multiple Linear Regression model with $\Delta ln(lon\_hhspe)_t$ as dependent variable and $\Delta ln(lon\_gva^*)_t$ and $\Delta ln(lon\_hhinc^*)_t$ as independent variables. Note that these two regressors would be obtained from Specification (1) and Specification (5), respectively.

[21] As opposed to VAR specifications which do not require a test for the individual significance of all variables in the model (Carriero, 2019).
[22] VECM requires Maximum Likelihood estimation of the parameters rather than OLS methodology.

4 Data description

This section is aimed at providing more detail on the samples, variables, and data used in the econometric models described throughout section 3.

Firstly, Specifications (1) to (6) have been estimated through samples all starting in the first quarter 1999, as London's real GVA and other relevant time series employed in this work are only available from first quarter 1998 in levels. Therefore, up to date, all new GLAE models consist of a sample of at least 20 years, i.e., a minimum of 80 observations. This number of observations is theoretically more than sufficient to produce medium-term forecasts with quarterly data. Sampling method is recursive so sample size will increase over time.

Secondly, looking at the variables employed in the new GLAE forecast models, a more detailed information of the data and its sources is provided in Table 1:

Table 1: Information of the variables employed in the new GLAE forecast models

Variable	Variable description	Data source	Data available from	Forecast calculation
lon_gva	London's real GVA (balanced approach), chained volume, 2016 prices, £million	ONS - Quarterly Country and Regional GDP Accounts from q1 2013 and GLAE estimations from q1 1998 to q4 2012[23]	q1 1998	GLAE forecast model
uk_gva	UK's real GVA at basic prices, chained volume measures, £million	ONS – UK Quarterly Economic Accounts	q1 1955	Based on OBR forecasts for UK's GDP growth rate
lon_wfj	Number of workforce jobs in London, £million	ONS - Labour Force Survey	q1 1971	GLAE forecast model
lon_prod	London's labour productivity calculated as London's real GVA(B) divided by working hours in London	ONS - Quarterly Country and Regional GDP Accounts and ONS - UK productivity hours and jobs (NUTS 1) from q1 2013. GLAE estimation of London's real GVA and ONS - UK productivity hours and jobs (NUTS 1) from q1 1998 to q4 2012.	q1 1998	Based on Experian forecasts of London's labour productivity
lon_hhspe	Total final consumption expenditure by London household, chained volume measures, 2016 prices, £million	Experian-UK. ONS data is only available at annual frequency	q1 1998	Based on Experian forecasts in Specification (1) and based on GLAE forecast model otherwise
lon_pmi	Purchase Managers Index for new business in London	IHS Markit	q1 1997	Based on a moving average of the last four quarters
uk_binv	UK's business investment – gross fixed capital formation, chained volume measures, £million	ONS - GDP first quarterly estimate time series (PN2)	q1 1997	Forecast is calculated using the historic average share of *uk_binv* within *uk_gva* (10.7%) as this share has remained broadly constant over time

[23] GLAE estimations for the mentioned period involve the 'quarterisation' of London's real GVA(B) annual estimates produced by the ONS based on the dynamics of quarterly real GDP for the UK. For more detail on this method see Keijonen and Lohuizen (2016).

Variable	Variable description	Data source	Data available from	Forecast calculation
lon_hhinc	Total disposable income in London household, chained volume measures, 2016 prices, £million	Experian-UK. ONS data is only available at annual frequency	q1 1998	Based on GLAE forecast model
uk_hhinc	Total disposable income in UK household, chained volume measures, 2016 prices, £million	ONS - UK Quarterly Economic Accounts	q1 1955	Based on OBR forecasts of total nominal disposable income in UK household divided by OBR forecasts of UK's inflation
lon_gva_i	London's real GVA (balanced approach) by industry, chained volume, 2016 prices, £million	ONS - Quarterly Country and Regional GDP Accounts from q1 2013 and GLAE estimations from q1 1998 to q4 2012[21]	q1 1998	GLAE forecast model
uk_gva_i	UK's real GVA by industry at basic prices, chained volume measures, £million	ONS - UK Quarterly Economic Accounts	q1 1990	Based on Experian forecasts of UK's GDP growth rate by industry
lon_wfj_i	Number of workforce jobs by industry in London, £million	ONS - Labour Force Survey	q1 1996	GLAE forecast model
lon_prod_i	London's labour productivity by industry calculated as London's real GVA(B) by industry divided by London's workforce jobs by industry, £million by workforce job	ONS - Quarterly Country and Regional GDP Accounts and ONS - Labour Force Survey from q1 2013. GLAE estimations of London's real GVA(B) and ONS - Labour Force Survey from q1 1998 to q4 2012	q1 1998	Based on Experian forecasts of London's labour productivity by industry

Source: Own elaboration.

Most variables shown in Table 1 are, by default, seasonally adjusted in its original sources. In the few time series where this could not be confirmed (*lon_pmi*, *lon_hhinc*, *lon_hhspe*), the seasonal adjustment to the raw data was applied by using Tramo-Seats[24].

Finally, the list of twenty industries estimated in Specification (2) and Specification (4) is provided below in Table 2. The criteria for the selection of these twenty sectors is the ONS Standard Industrial Classification[25] for both the national and London variables. It is important to point out that raw data for London industries generally present a higher variance than the aggregate time series as it can be checked in Table A3 in the Annex. This feature of the data might undermine the performance of forecasts in Specification (2) and Specification (4) when compared to other models.

[24] More detail on this technique can be found here.
[25] Further information on this classification can be found on the ONS website.

Table 2: List of industries in GLAE forecasts

1. Agriculture, forestry, and fishing	11. Financial and insurance activities
2. Mining and quarrying	12. Real estate activities
3. Manufacturing	13. Professional, scientific, and technical activities
4. Electricity, gas, steam, and air-conditioning supply	14. Administrative and support service activities
5. Water supply; sewerage and waste management	15. Public administration and defence; compulsory social security
6. Construction	16. Education
7. Wholesale and retail trade; repair of motor vehicles	17. Human health and social work activities
8. Transportation and storage	18. Arts, entertainment, and recreation
9. Accommodation and food service activities	19. Other service activities
10. Information and communication	20. Activities of household

Source: Own elaboration based on ONS information.

5 Performance of the new GLAE forecast models

In this chapter, the performance of the new GLAE forecast models will be evaluated against the purposes for which they were created – i.e., improved accuracy and robustness -. This evaluation consists in the following three-step procedure: Firstly, the new models are compared to the old GLAE forecast models in terms of both point and density forecasting accuracy[26] for a range of in-sample periods. Secondly, the new models are assessed against outturn data but also against independent forecasts produced by a prestigious global economic consultancy – which is the only comparable source of medium-term forecasts for London's economy using quarterly data –. For confidentiality purposes, the name of this company will not be shown in this document and will be replaced by 'IF' which stands for 'independent forecaster'. Finally, an impulse-response analysis is provided as an additional check for the robustness of Specification (1), Specification (3), and Specification (6).

5.1 Evaluation against the old GLAE forecast models

In this step, the forecasting performance of Specifications (1) to (6) relative to the old GLAE methodology is assessed. For simplification, only the four main industries within London's economy - real estate activities (*re*); financial and insurance activities (*fin*); professional, scientific, and technical activities (*prof*); and information and communication (*ic*) -[27] are shown for the sectoral models – Specification (2) and Specification (4) – although results are consistent with the remaining industries. The approach chosen by Carriero et al. (2019) was found suitable to be replicated in this work as it compounds an updated vision of the existing evaluation methods with regards to forecasting models. This approach consists in measuring point and density forecasts relative performance through 'root mean squared forecast error' (*RMSFE*) and 'median logscore' (MLS)[28], respectively. These forecasting evaluation measures can be formally expressed as:

relative RMSFE (rRMSFE) = 1 – $\frac{NEW\ RMSFE}{OLD\ RMSFE}$, where *RMSFE* = $\sum_{t=1}^{12}[\frac{(y-y*)^2}{12}]^{1/2}$ and $y - y*$ equals the forecast error.

relative MLS (rMLS) = 1 + [(– *OLD MLS*) – (– *NEW MLS*)], where *MLS* equals the error (in logs) between the actual value of the dependent variable and its median expected value given a probability distribution.

To provide a consistent evaluation, the above two measures were applied across five random-selected samples starting in the third quarter of 2006[29]. In line with GLAE out-of-sample estimates, the forecasting horizon was set in three years – twelve quarters – for all in-sample simulations.

[26] Density forecasts include the probability distribution of the expected value for a given period.
[27] These four industries represented 54.8% of total real GVA(B) generated in London in 2018, according to ONS Regional Accounts data.
[28] As stated in Carriero et al. (2019), *"median* is preferred to *mean logscore* in order to minimize the impact of outliers. Outlier values are more frequent with logscores than with squared forecast errors".
[29] This starting date allows samples to contain a sufficient number of observations for producing reliable forecasts.

Table 3: Relative performance of the new GLAE forecast models to the old GLAE forecast models

	q3 2006 – q2 2009	q4 2008 – q3 2011	q2 2012 – q1 2015	q3 2014 – q2 2017	q1 2016 – q4 2018	Mean
***rRMSFE* (1)**	0.61***	0.54**	0.70***	0.72***	0.71***	0.66
***rMLS* (1)**	-2.41***	-2.01**	-2.49***	-3.24***	-3.31***	–
***rRMSFE* (2_{re})**	0.58**	0.64***	0.70***	0.67***	0.75***	0.69
***rMLS* (2_{re})**	-1.57**	-1.58**	-1.61**	-1.61**	-1.63**	–
***rRMSFE* (2_{fin})**	0.64***	0.57**	0.66***	0.62***	0.74***	0.65
***rMLS* (2_{fin})**	-1.67**	-1.68**	-1.72**	-2.10***	-2.08***	–
***rRMSFE* (2_{prof})**	0.41**	0.36**	0.42**	0.45**	0.45**	0.51
***rMLS* (2_{prof})**	-1.21**	-1.23**	-1.25**	-1.24**	-1.23**	–
***rRMSFE* (2_{ic})**	0.35	0.36*	0.33	0.38*	0.41*	0.37
***rMLS* (2_{ic})**	-1.37*	-1.45	-1.51	-1.78*	-1.84*	–
***rRMSFE* (3)**	0.62***	0.64***	0.76***	0.78***	0.75***	0.71
***rMLS* (3)**	-3.20***	-3.11***	-3.49***	-3.54***	-3.52***	–
***rRMSFE* (4_{re})**	0.54*	0.63***	0.62*	0.71***	0.75***	0.65
***rMLS* (4_{re})**	-1.77**	-1.79**	-2.00**	-2.54***	-2.33**	–
***rRMSFE* (4_{fin})**	0.74***	0.77***	0.76***	0.72***	0.68***	0.75
***rMLS* (4_{fin})**	-1.94**	-2.16**	-2.47**	-2.71***	-2.98***	–
***rRMSFE* (4_{prof})**	0.51	0.66**	0.72**	0.75**	0.65***	0.66
***rMLS* (4_{prof})**	-1.51*	-1.28**	-1.54**	-1.62**	-1.62**	–
***rRMSFE* (4_{ic})**	0.71***	0.75***	0.69***	0.65***	0.70***	0.70
***rMLS* (4_{ic})**	-2.58***	-2.45**	-2.31**	-2.78***	-3.20***	–
***rRMSFE* (5)**	0.49	0.52*	0.49*	0.54**	0.55**	0.53
***rMLS* (5)**	-1.49*	-1.52	-1.67*	-1.94**	-2.15**	–
***rRMSFE* (6)**	0.53**	0.61***	0.60***	0.65***	0.67***	0.61
***rMLS* (6)**	-2.70***	-2.81***	-3.09***	-3.34***	-3.33***	–
Number of observations	30	39	53	62	68	–

*Source: Own elaboration based on Eviews outcomes. In parenthesis, the model specification as described in section 3 of this paper. Values smaller than one imply that new GLAE model improves over the old GLAE model. *Indicate rejection of the null hypothesis of no statistical difference at 90% confidence level. **Indicate rejection of the null hypothesis of no statistical difference at 95% confidence level. ***Indicate rejection of the null hypothesis of no statistical difference at 99% confidence level.*

Table 3 shows the results of the relative performance of the new GLAE models to the old models in terms of both point *(rRMSFE)* and density forecasts *(rMLS)*. As it can be observed, all values in Table 3 are lower than one which indicates that new forecasts are more accurate on average – i.e., present less errors - than the old models for the selected measures and samples. Besides, except for some periods in Specification (5) and the models by industry, all those improvements are statistically significant at a minimum of 90% confidence which proves that the difference in forecasting accuracy between the two methodologies is not the result of an stochastic process. Looking at point forecasts only, the new models improve forecasting accuracy - on average for the selected periods - by 66% and 71% in Specification (1) and Specification (3), respectively, when compared to the old GLAE models. This improvement reaches 53% and 61% in Specification (5) and Specification (6), respectively. By industries, results are more volatile but follow the aggregate pattern of even larger improvement in workforce jobs than real GVA forecasts. Thus, the smallest average improvement for sectoral modelling is 37% in real GVA for the *ic* industry. Regarding density forecasts performance, this generally goes in line with the corresponding point forecasts performance. The *rMLS* measure does not allow a precise calculation of the improvement like *rRMSFE* does, but all *rMLS* figures are below one which indicates improvement and this difference is statistically significant for the wide majority of selected cases. Therefore, it can also be concluded that density forecasts with the new GLAE models are less biased than what old GLAE models would predict.

5.2 Evaluation against outturn data and an independent forecaster

In the sub-section above, it has been shown that the new GLAE forecast models improve performance over the previous GLAE methodology, which is the main purpose of this study. However, how do the new models perform against the actual time series? And against an authoritative independent private forecaster (IF)[30] which provides the only comparable estimates, based on a GE model?

These questions have been analysed in this subsection for the same sample periods, industries, and forecasting horizon selected in the subsection 5.1. Here, the new GLAE models and IF forecasts are compared against outturn data[31] which indirectly enables a comparison between the two forecasting methodologies as well. As IF does not provide density forecasts in its publications, the current evaluation focuses on point forecasts only[32]. Thus, the following two classic point forecasting error measures have been employed:

Root mean squared forecast error (*RMSFE*), as described in subsection 5.1 of this paper.

Mean absolute percentage error (*MAPE*) = $\frac{1}{12}\sum_{t=1}^{12} | \frac{y*-y}{y*} |$, where y^* is the actual value and y is the predicted value.

[30] Identity of this British forecaster will remain hidden in this document due to GLA data protection rules.
[31] Note that for Specification (5) and Specification (6) there exists no official quarterly series of the dependent variable, so quarterly forecasts released by Experian-UK in December 2019 have been assumed as outturn data for the purposes of this study.
[32] IF point forecasts were obtained from the most recent IF publication prior to the five selected forecasting periods. This method might incorporate deviations to the current IF forecasts if the historic series had been revised since those publications. Despite this potential limitation, the simulation conducted here is thought to be a good approximation of the performance of IF forecasts.

Table 4: Relative performance of new GLAE forecast models and IF forecasts to outturn data as measured by *MAPE*

	q3 2006 – q2 2009	q4 2008 – q3 2011	q2 2012 – q1 2015	q3 2014 – q2 2017	q1 2016 – q4 2018	Mean
GLAE (1)	0.23	0.26	0.29	0.20	0.19	0.23
IF (1)	0.22	0.31	0.35	0.47	0.56	0.38
GLAE (2_{re})	0.59	0.36	0.47	0.44	0.49	0.47
IF (2_{re})	0.51	0.65	0.74	0.49	0.61	0.60
GLAE (2_{fin})	0.27	0.29	0.39	0.30	0.28	0.30
IF (2_{fin})	0.25	0.26	0.28	0.40	0.33	0.31
GLAE (2_{prof})	0.37	0.44	0.45	0.33	0.37	0.39
IF (2_{prof})	0.41	0.44	0.45	0.50	0.47	0.45
GLAE (2_{ic})	0.53	0.48	0.49	0.47	0.47	0.49
IF (2_{ic})	0.53	0.52	0.53	0.54	0.53	0.53
GLAE (3)	0.20	0.20	0.19	0.22	0.21	0.20
IF (3)	0.51	0.53	0.49	0.46	0.48	0.49
GLAE (4_{re})	0.60	0.62	0.61	0.61	0.58	0.60
IF (4_{re})	0.65	0.80	0.84	0.65	0.71	0.73
GLAE (4_{fin})	0.39	0.38	0.39	0.38	0.38	0.38
IF (4_{fin})	0.45	0.49	0.42	0.52	0.45	0.47
GLAE (4_{prof})	0.43	0.41	0.44	0.34	0.37	0.40
IF (4_{prof})	0.42	0.41	0.44	0.39	0.40	0.41
GLAE (4_{ic})	0.50	0.50	0.49	0.48	0.47	0.49
IF (4_{ic})	0.52	0.62	0.49	0.53	0.53	0.54
GLAE (5)	0.32	0.30	0.26	0.27	0.27	0.28
IF (5)	0.22	0.21	0.22	0.21	0.21	0.21
GLAE (6)	0.19	0.19	0.21	0.21	0.20	0.20
IF (6)	0.16	0.16	0.15	0.17	0.16	0.16
Number of observations	30	39	53	62	68	–

Source: Own elaboration based on Eviews outcomes. In parenthesis, the model specification as described in section 3 of this paper.

Table 4 shows the relative performances of both GLAE and IF forecast models to outturn data[33], according to the *MAPE* measure. Results deriving from the *RMSFE* method are broadly equivalent and, to avoid repetition, can be seen separately in Table A4 of the Annex. Table 4 indicates that, for the selected in-sample simulations, the new GLAE forecasts present between a 20% and 23% absolute error – on average – with respect to outturn data for the headline models. Specification (1), Specification (3), and Specification (6) perform very similarly and over the other models despite some differences across model samples. Errors in Specification (5) are slightly higher which might be associated with the use of a Multiple Linear Regression model rather than VAR modelling. *MAPE* can vary from 30% to 60% - on average - when forecasting real GVA or workforce jobs for some industries, probably due to the higher variance in the raw data by industries as already explained in section 4. No consensus was found in the literature on what maximum *MAPE* is desirable for a forecast model although it seems obvious that the lower *MAPE*, the better.

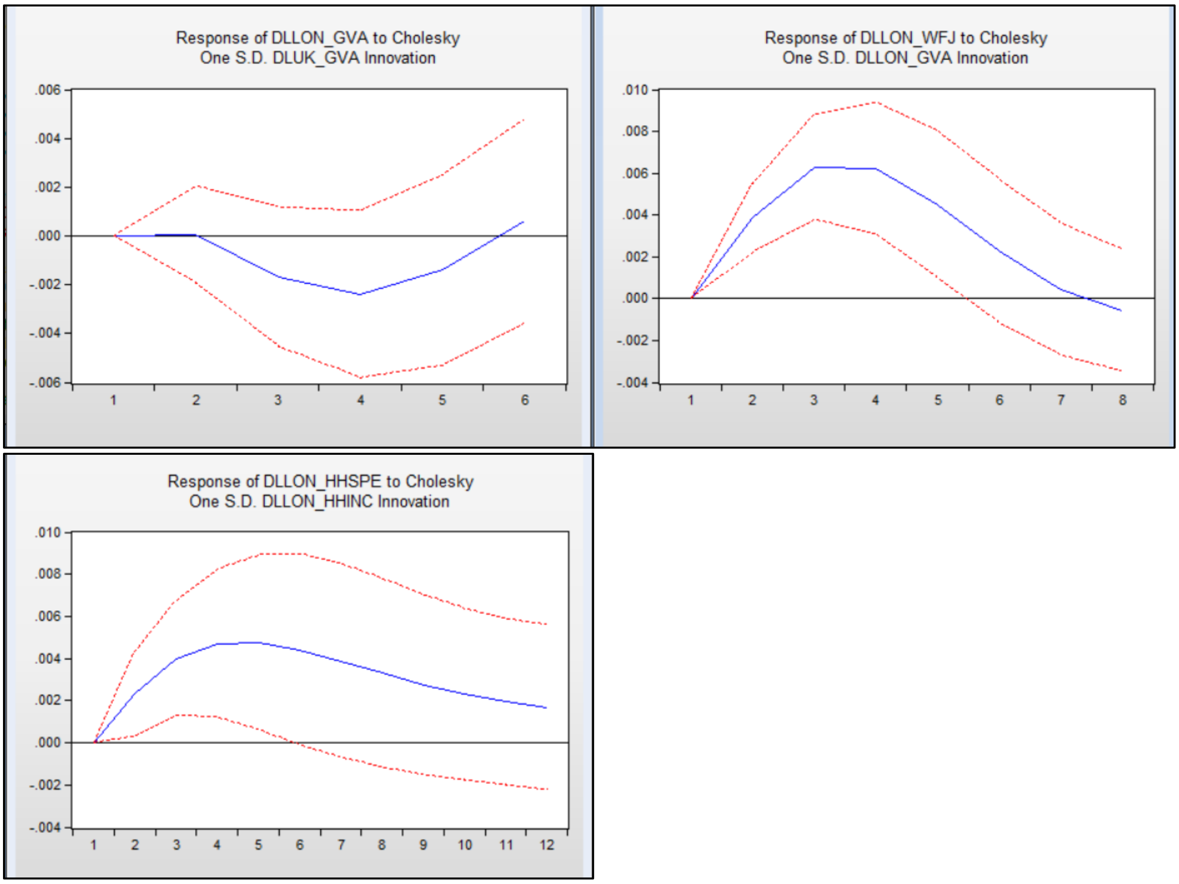
[33] Outturn data as at 8 February 2020. It is important to point out that historic data in time series are frequently subject to revisions, in which case, the performance of GLAE forecasting models can differ from the results presented in this study.

Results in Table 4 also allow the assessment of the relative performance of the new GLAE models against their only reference – IF forecasts –. This analysis suggests that GLAE forecasts seem to overcome – on average and for the selected samples – IF forecasts for all models except for Specification (5) and Specification (6). However, even in these two cases the difference in *MAPE* does not exceed 7 percentage points looking at the average performance across samples. *MAPE* for GLAE models is lower by 15 and 29 percentage points – on average - than IF models for Specification (1) and Specification (3), respectively, which are the most relevant models in this study. Looking at the models by industry, the difference between the two methodologies is generally narrower and even close to zero in some cases. Overall, the evidence that can be extracted from Table 4 suggests that IF forecasts only perform similarly or slightly better than GLAE forecasts for a reduced number of dependent variables and samples, given the selected forecasting horizon of twelve quarters.

5.3 Evaluation under a perturbation within the model

Having evaluated the performance of the new GLAE forecast models against the old GLAE methodology, a comparable external forecaster, and outturn data, this section ends with an additional robustness test to the new models. This check would complement the tests for residuals, stationarity of the variables, and optimal lag length already commented in section 3 of this paper. The additional analysis consists in an impulse-response simulation in Specification (1), Specification (3), and Specification (6), which are the econometric models that allow this type of test – besides the sectoral models –. Impulse-response analyses let explain the present and future reaction of variables of interest within VAR models to a shock - also called perturbation or innovation – produced in other variables within the model. For simplification purposes, the shock was simulated only on the main determinants of the variables of interest in the aforementioned Specifications. The results provided by *Eviews* are shown in Figure 1.

Figure 1: Impulse-response results for Specification (1), Specification (3), and Specification (6)



Source: Own elaboration based on Eviews outcomes. Blue lines are the impulse-response functions (IRFs) and red lines are the 95% confidence intervals for those IRFs. Vertical axis indicates the impact of the shock on the variable of interest while horizontal axis is the number of quarters after the shock took place (i.e., shock is assumed to happen in t=0). Eviews uses a Cholesky decomposition method for estimating IRFs along with a Monte-Carlo simulation based on 1000 repetitions of the experiment.

The evaluation of the impulse-response results has followed the approach suggested by Chudik et al. (2019) which, despite recognizing differences among models, focuses on three common elements to confirm the robustness of a VAR model for forecasting purposes: 1) A plausible sign and cumulated effect of the shock on the variable of interest, 2) shock impact starting in connection with the VAR order, and 3) shock effect gradually decaying over time towards 0 (i.e., the perturbation impact cannot be permanent).

Top-left chart in Figure 1 refers to Specification (1) and represents the reaction of London's real GVA annualised growth rate (*dllon_gva*) given a negative perturbation by one standard deviation in UK's real GVA annualised growth rate (*dluk_gva*). Under that scenario, *dllon_gva* would be broadly unaffected for the subsequent two quarters after the shock took place, as it can be expected given that Specification (1) is a third-order VAR model[34]. *dllon_gva* would decline during the third and fourth quarters reaching a cumulative fall above 0.2 percentage points, but the shock effect is temporary. In *t+5* the variable starts recovering and ends up returning to its steady-state one year and a half after the perturbation took place.

Top-right chart in Figure 1 refers to Specification (3) and shows the response of the annualised growth rate in London's workforce jobs (*dllon_wfj*) given a positive shock by one standard deviation in the London's real GVA annualised growth rate (*dllon_gva*). In this simulation, *dllon_wfj* would start being affected by the

[34] Note that this is the default scenario under a shock equals to one standard deviation (relatively small). If the shock was substantially larger than one deviation, we would expect some effect on *dllon_gva* in the first two quarters as well although always proportionally smaller than the effect in *t+3*.

perturbation two quarters after the shock took place – Specification (3) is a second-order VAR - and the cumulated effect might increase the variable of interest by over 0.6 percentage points at the end of the third period. After a quarter of stabilisation, *dllon_wfj* would return to its pre-shock level between seven and eight quarters after the innovation took place. Consequently, in Specification (3), a shock would have a bit longer and more intense effect on the dependent variable of interest than for Specification (1). This fact might be explained because of the larger explicative power of *dllon_gva* in Specification (3) – as *dllon_gva* is the only endogenous variable in the model except the variable of interest – over *dluk_gva* in Specification (1).

Finally, the bottom-left chart in Figure 1 refers to Specification (6) and illustrates the behaviour of the annualised growth rate of London household real expenditure (*dllon_hhspe*) to a positive innovation by one standard deviation in the annualised growth rate of London household real income (*dllon_hhinc*). As in the previous simulation, Specification (6) is a second-order VAR model so the effect of the shock on *dllon_hhspe* is not appreciated at the first quarter. During the second and third quarters, *dllon_hhspe* would experience a cumulative positive impact of more than 0.4 percentage points. This effect would remain constant in *t+4* and start declining towards the pre-shock level afterwards. As opposed to Specification (1) and Specification (3), the convergence towards the steady-state happens more slowly in this model, which might be explained because there are no exogenous variables compensating the impact of the shock in Specification (6).

To sum up, the analysis of the impulse-response test for Specification (1), Specification (3), and Specification (6) suggests that these models are robustly designed for forecasting.

6 Conclusions

GLAE has been publishing medium-term forecasts for Greater London's economy since 2003. This study explains a recent structural change in the GLAE forecasting methodology, aimed at improving both accuracy and robustness with respect to the previous approach.

Despite several limitations such as a relatively scarce academic literature on regional economic forecasting and UK regional series being often unavailable, insufficient in terms of historic data, released with a long delay, or statistically irrelevant for forecasting purposes, new GLAE forecast models have been robustly built using VAR modelling. As an exception, the forecast model for household real income relies on a Multiple Linear Regression method.

The new models improve point forecasting accuracy between 66% and 71% - on average – for London's Real GVA and London's workforce jobs when compared to the old GLAE models. This improvement reaches between 53% and 61% for forecasts of household real income and household real expenditure in London. By London industries, results are more volatile but the smallest average improvement is 37%. Density forecasts perform similarly to point forecasts in terms of accuracy. Looking at the performance against outturn data, the new GLAE forecasts show between 20% and 23% absolute error – on average – for the headline models. Due to the higher variance in the raw data, this error increases from 30% to 60% - on average - when forecasting real GVA or workforce jobs by industries in London. There is no consensus in the literature on how to interpret error percentage figures objectively, but the only comparable forecasts do not perform better – overall – than the new GLAE forecasts.

Further improvements in the performance of GLAE forecasts for London's economy will narrowly depend on overcoming the aforementioned limitations in the future, especially for the case of variables other than GVA. Besides, achieving these improvements might result particularly challenging in periods of high-uncertainty - such as the present year - regardless of the econometric approach chosen.

Either way, GLAE will not weaken efforts to ensure that its forecast models are in line with best practice wherever they are used and to improve in tandem the quality of London economic statistics and their forecasting methodology.

Annex

Table A1: Johansen Cointegration tests for: 1) London's real GVA and UK's real GVA, 2) London's real GVA and London's workforce jobs, and 3) London household real expenditure and London household real income

1) Series: London's real GVA and UK's real GVA				
Sample: q1 1998 – q4 2021				
Included observations (after adjustments): 83				
Lags interval: 1 to 2				
Selected (0.05 level*) number of cointegrating relations by model				
Data trend:	None	None	Linear	Linear
Test type:	**No intercept / no trend**	**Intercept / no trend**	**Intercept / no trend**	**Intercept / trend**
Trace:	**0**	**0**	**0**	**0**
Max. eigenvalue:	**0**	**0**	**0**	**0**
*Critical values based on MacKinnon-Haug-Michelis (1999)				

2) Series: London's real GVA and London's workforce jobs				
Sample: q1 1998 – q4 2021				
Included observations (after adjustments): 83				
Lags interval: 1 to 2				
Selected (0.05 level*) number of cointegrating relations by model				
Data trend:	None	None	Linear	Linear
Test type:	**No intercept / no trend**	**Intercept / no trend**	**Intercept / no trend**	**Intercept / trend**
Trace:	**0**	**0**	**0**	**0**
Max. eigenvalue:	**0**	**0**	**0**	**0**
*Critical values based on MacKinnon-Haug-Michelis (1999)				

3) Series: London household real expenditure and London household real income				
Sample: q1 1998 – q4 2021				
Included observations (after adjustments): 77				
Lags interval: 1 to 2				
Selected (0.05 level*) number of cointegrating relations by model				
Data trend:	None	None	Linear	Linear
Test type:	**No intercept / no trend**	**Intercept / no trend**	**Intercept / no trend**	**Intercept / trend**
Trace:	**1**	**1**	**0**	**0**
Max. eigenvalue:	**1**	**1**	**0**	**0**
*Critical values based on MacKinnon-Haug-Michelis (1999)				

Source: Own elaboration based on Eviews outcomes. Johansen Cointegration tests for the relevant variables only show a cointegrating relationship with no trend for London household real expenditure and London household real income at 95% confidence level.

Table A2: Estimation results of Specification (5)

Dependent variable: Annual growth rate of household real income in London				
Method: Ordinary Least Squares (OLS)				
Sample (adjusted): q4 1999 – q4 2017				
Included observations: 73 after adjustments				
Independent variable	**Coefficient**	**Standard error**	**T-statistic**	**P-value**
Constant	0.0109	0.0026	4.1093	**0.0001**
Annual growth rate of household real income in the UK	0.9582	0.0736	13.0078	**0.0000**
Annual growth rate of London's real GVA lagged by three quarters	0.2049	0.0511	4.0040	**0.0002**
R-squared	0.7405			
Adjusted R-squared	0.7331			
Mean dependent variable	0.0384			
Standard deviation dependent variable	0.0256			

Source: Own elaboration based on Eviews outcome. All selected independent variables are significant at 99% confidence in this Multiple Linear Regression model.

Table A3: Standard deviation of selected London variables

Variable	**Standard deviation**
lon_wfj	0.005
lon_gva	0.011
lon_wfj_{fin}	0.013
lon_wfj_{re}	0.014
lon_wfj_{prof}	0.019
lon_wfj_{ic}	0.021
lon_gva_{re}	0.030
lon_gva_{prof}	0.030
lon_gva_{ic}	0.051
lon_gva_{fin}	0.077

Source: Own elaboration. All variables are in annualised growth rates. Variables have been sorted by descending order based on its standard deviation. For simplification, only the four main industries of London's economy are shown.

Table A4: Relative forecasting performance of new GLAE forecast models and IF forecasts to outturn data as measured by *RMSFE*

	q3 2006 – q2 2009	q4 2008 – q3 2011	q2 2012 – q1 2015	q3 2014 – q2 2017	q1 2016 – q4 2018	Mean
GLAE (1)	0.0062	0.0082	0.0091	0.0058	0.0052	0.0069
IF (1)	0.0059	0.0098	0.0110	0.0136	0.0153	0.0111
GLAE (2_{re})	0.0140	0.0096	0.0170	0.0110	0.0125	0.0128
IF (2_{re})	0.0121	0.0173	0.0268	0.0123	0.0156	0.0168
GLAE (2_{fin})	0.0081	0.0091	0.0105	0.0094	0.0081	0.0090
IF (2_{fin})	0.0074	0.0082	0.0075	0.0125	0.0095	0.0090
GLAE (2_{prof})	0.0101	0.0115	0.0117	0.0090	0.0100	0.0105
IF (2_{prof})	0.0111	0.0115	0.0117	0.0136	0.0127	0.0121
GLAE (2_{ic})	0.0163	0.0127	0.0129	0.0123	0.0123	0.0133
IF (2_{ic})	0.0163	0.0138	0.0140	0.0141	0.0139	0.0144
GLAE (3)	0.0059	0.0059	0.0056	0.0065	0.0062	0.0060
IF (3)	0.0150	0.0156	0.0144	0.0136	0.0142	0.0146
GLAE (4_{re})	0.0082	0.0088	0.0085	0.0085	0.0080	0.0084
IF (4_{re})	0.0089	0.0114	0.0117	0.0091	0.0098	0.0102
GLAE (4_{fin})	0.0093	0.0111	0.0117	0.0099	0.0108	0.0106
IF (4_{fin})	0.0107	0.0143	0.0126	0.0135	0.0128	0.0128
GLAE (4_{prof})	0.0110	0.0107	0.0112	0.0095	0.0104	0.0106
IF (4_{prof})	0.0107	0.0107	0.0112	0.0109	0.0112	0.0109
GLAE (4_{ic})	0.0164	0.0188	0.0145	0.0170	0.0169	0.0167
IF (4_{ic})	0.0171	0.0233	0.0145	0.0188	0.0191	0.0186
GLAE (5)	0.0099	0.0095	0.0084	0.0087	0.0087	0.0090
IF (5)	0.0068	0.0067	0.0071	0.0068	0.0068	0.0068
GLAE (6)	0.0050	0.0051	0.0058	0.0058	0.0054	0.0054
IF (6)	0.0042	0.0043	0.0041	0.0047	0.0043	0.0043
Number of observations	30	39	53	62	68	–

Source: Own elaboration based on Eviews outcomes.

References

Artola, C., A. Fiorito, M. Gil, J. Perez, A. Urtasun, and D. Vila (2018). "Monitoring the Spanish Economy from a Regional Perspective: Main Elements of Analysis", Banco de España, Occasional Paper Series nº 1809.

Bäurle, G., E. Steiner, and G. Züllig (2018). "Forecasting the production side of GDP", Swiss National Bank, Working Papers 2018-16.

Bell, D. (1993). "Regional Econometric Modelling in the UK: A Review", Regional Studies, 27:8, 777-782.

Bok, B., D. Cratelli, D. Giannone, A. Sbordone, and A. Tambalonni (2017). "Macroeconomic Nowcasting and Forecasting with Big Data" Federal Reserve Bank of New York, Staff Reports 837-2017.

Caraiani, P. (2018). "Forecasting Romanian GDP Using a BVAR Model", Journal for Economic Forecasting, Institute for Economic Forecasting, vol. 0(4), pages 76-87.

Carriero, A., A. Galvao, and G. Kapetanios (2019). "A comprehensive evaluation of macroeconomic forecasting methods", International Journal of Forecasting nº 35, 1226–1239.

Chauvet, M., and P. Simon (2012). "Forecasting output", Handbook of Economic Forecasting, Volume 2.

Chernis, T., C. Cheung, and G. Velasco (2017). "A Three-Frequency Dynamic Factor Model for Nowcasting Canadian Provincial GDP Growth", Bank of Canada, Staff Discussion Paper 2017-8.

Chudik, A., and G. Georgiadis (2019). "Estimation of Impulse Response Functions When Shocks are Observed at a Higher Frequency than Outcome Variables", Globalization Institute Working Paper 356.

D'Agostino, A., L. Gambetti, and D. Giannone (2013). "Macroeconomic forecasting and structural change", Journal of Applied Econometrics, 28, 82–101.

Devarajan, S., S. Delfin, D. Lewis, S. Robinson, and P. Sinko (1997). "Simple General Equilibrium Modelling", Cambridge University Press.

Douglass, G., and M. Keijonen (2016). "The historic performance of the GLA's medium-term economic forecast model", GLA Economics, Current Issues Note 49.

Galí, J. (2008). "Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and Its Applications", Princeton University Press.

Gil, M., D. Leiva-Leon, J. Perez, and A. Urtasun (2019). "An application of dynamic factor models to nowcast regional economic activity in Spain", Banco de España, Occasional Paper Series nº 1904.

GLA Economics (2019). "London's Economic Outlook", December.

Grant, A., G. Koop, S. Mcintyre, and P. Smith (2015). "Nowcasting Scottish GDP Growth", Scottish Institute for Research in Economics, Discussion Paper 2015-08.

Henzel, S., R. Lehmann, and K. Wohlrabe (2016). "Nowcasting Regional GDP: The Case of Free State of Saxony", Review of Economics, 66(1), 71-98.

Keijonen, M., and A. Van Lohuizen (2016). "Modelling real quarterly GVA data for London", GLA Economics, Current Issues Note 50.

Kiviet., J. (2012). "Monte Carlo Simulation for Econometricians", Foundations and Trends in Econometrics, vol. 5, 1–2, pp 1-181.

Koop, G., S. Mcintyre, J. Mitchell, and A. Poon (2018). "Regional Output Growth in the United Kingdom: More Timely and Higher Frequency Estimates, 1970-2017", Economic Statistics Centre of Excellence, Discussion Paper 2018-14.

Lehmann, R. and K. Wohlrabe (2013). "Forecasting GDP at the Regional Level with Many Predictors", German Economic Review, 16(2), 226-254.

National Institute of Economic and Social Research (2018a). "National Institute Global Econometric Model: An overview", NiGEM Review Articles, October.

Rossi, B. (2014). "Density forecasts in economics and policymaking", Centre de Recerca en Economia Internacional, Els Opuscles del CREI nº 37.

Sdrakas, N. (2003). "VAR modelling of the euro area GDP on the basis of principal component analysis", Eurostat Working Papers and Studies, October.

Stock, J. (2005). "Symposium on Regional Economic Indicator", Review of Economics and Statistics, 87, 593.

Wan, X. and H. Kai (2014). "Nowcasting and Short-term Forecasting of Chinese Quarterly GDP: Mixed Frequency Approach", The Anthropologist, 17:1, 53-63.

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