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ABSTRACT

The aim of this paper is to apply single equation dynamic models together with information from a large dataset of predictors in the construction of short-term growth forecasts for the production-side components of the national accounts, i.e. Gross Value Added of sectors, and import duties plus Value Added Tax. To summarise the information content in a large number of predictors, we employ techniques such as common factors and forecast combinations. Aggregate and component forecasts are computed under two approaches to forecasting GDP growth, namely a direct and a bottom-up approach. In the direct approach, unconstrained models for GDP growth are estimated to compute forecasts for the aggregate, while constrained component models are used to obtain the disaggregate forecasts, which add up to the GDP growth forecasts computed directly. In the bottom-up approach, unconstrained component models are estimated to compute growth forecasts for the components as well as for GDP growth by adding up the unconstrained component forecasts. The performance of aggregate and disaggregate forecasts from the two approaches is assessed via pseudo out-of-sample exercises. The results show that the use of macroeconomic and financial predictors improves on the accuracy of the naïve forecasts for most production-side components and the aggregate, under both the direct and bottom-up approaches. GDP growth forecasts from the direct approach are somewhat superior to those from the bottom-up approach. Both approaches result in gains in forecasting growth in industry, construction, trade, financial activities and duties. In the sector of professional services gains are limited for both constrained and unconstrained forecasts. In the sectors of agriculture and public administration, education and health, neither the unconstrained models nor the constrained sectoral models significantly improve on the naïve benchmark. Compared to the unconstrained component forecasts, gains attained through constrained forecasts are slightly lower, but more widespread across components and horizons.

Keywords: forecasting, combination forecasts, GDP, gross value added, bottom-up forecasts.

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ΠΕΡΙΛΗΨΗ

Στόχος του άρθρου είναι η εφαρμογή δυναμικών μοντέλων μίας εξίσωσης, σε συνδυασμό με πληροφορίες από μια εκτεταμένη βάση δεδομένων, για την κατασκευή βραχυπρόθεσμων προβλέψεων του ρυθμού μεταβολής της οικονομικής δραστηριότητας σε τομείς της κυπριακής οικονομίας. Συγκεκριμένα, κατασκευάζονται προβλέψεις για τον ρυθμό μεταβολής της ακαθάριστης προστιθέμενης αξίας (σε σταθερές τιμές) των τομέων και των εισαγωγικών δασμών και ΦΠΑ, δηλαδή για όλες τις συνιστώσες του ΑΕΠ, από την πλευρά της προσφοράς, όπως παρουσιάζονται στους τριμηνιαίους εθνικούς λογαριασμούς. Η πληροφόρηση που περιέχεται στον μεγάλο αριθμό δεικτών που χρησιμοποιούνται, συνοψίζεται με τη χρήση οικονομετρικών τεχνικών όπως οι κοινοί παράγοντες και οι συνδυασμοί προβλέψεων.

Οι προβλέψεις για τον ρυθμό μεταβολής του ΑΕΠ και των συνιστωσών του υπολογίζονται χρησιμοποιώντας δύο εναλλακτικές προσεγγίσεις: (α) την άμεση πρόβλεψη του ρυθμού μεταβολής του ΑΕΠ και (β) την έμμεση πρόβλεψη του ρυθμού μεταβολής του ΑΕΠ. Στην προσέγγιση της άμεσης πρόβλεψης, εκτιμώνται μοντέλα για τον ρυθμό μεταβολής του ΑΕΠ, χωρίς οποιουσδήποτε περιορισμούς, τα οποία χρησιμοποιούνται για να υπολογιστούν προβλέψεις για τον ρυθμό μεταβολής του ΑΕΠ. Για τις συνιστώσες του ΑΕΠ, εκτιμώνται μοντέλα υπό περιορισμούς βάσει των οποίων υπολογίζονται προβλέψεις για τις συνιστώσες οι οποίες αθροίζουν στις προβλέψεις του ρυθμού μεταβολής του ΑΕΠ που υπολογίστηκαν άμεσα από τα μοντέλα. Στην προσέγγιση της έμμεσης πρόβλεψης, εκτιμώνται μοντέλα για τις συνιστώσες του ΑΕΠ χωρίς οποιουσδήποτε περιορισμούς για να υπολογιστούν προβλέψεις για τον ρυθμό μεταβολής των συνιστωσών. Στη συνέχεια, οι προβλέψεις για το ΑΕΠ υπολογίζονται αθροίζοντας τις προβλέψεις των συνιστωσών που λήφθηκαν από τα μοντέλα χωρίς περιορισμούς. Η ακρίβεια των προβλέψεων που υπολογίζονται από τις δύο προσεγγίσεις αξιολογείται σε σχέση με προβλέψεις από απλοϊκά μοντέλα.

Τα αποτελέσματα δείχνουν ότι και στις δύο προσεγγίσεις, η χρήση μακροοικονομικών και χρηματοοικονομικών μεταβλητών βελτιώνει την ακρίβεια των προβλέψεων για τις περισσότερες συνιστώσες καθώς και για το ΑΕΠ. Οι προβλέψεις για τον ρυθμό μεταβολής του ΑΕΠ που υπολογίζονται με την άμεση προσέγγιση συνδέονται με μικρότερο σφάλμα συγκριτικά με τις αντίστοιχες προβλέψεις που υπολογίζονται μέσω της έμμεσης προσέγγισης. Και οι δύο προσεγγίσεις έχουν ως αποτέλεσμα ακριβέστερες προβλέψεις για τον ρυθμό ανάπτυξης στους τομείς της μεταποίησης, των κατασκευών, του εμπορίου και των χρηματοπιστωτικών δραστηριοτήτων καθώς και για τους δασμούς. Στον τομέα των επαγγελματικών υπηρεσιών οι βελτιώσεις στην ακρίβεια των προβλέψεων είναι οριακές και στις δύο προσεγγίσεις. Στους τομείς της γεωργίας και της δημόσιας διοίκησης, εκπαίδευσης και υγείας, ούτε η άμεση ούτε η έμμεση προσέγγιση οδηγούν σε σημαντικές μειώσεις του σφάλματος των προβλέψεων. Τα οφέλη σε όρους μειωμένου σφάλματος πρόβλεψης, είναι ελαφρώς μικρότερα στην περίπτωση των τομεακών προβλέψεων που υπολογίζονται με την άμεση προσέγγιση (δηλ. κάτω από περιορισμούς στα μοντέλα των συνιστωσών) συγκριτικά με τις τομεακές προβλέψεις που εκτιμώνται με την έμμεση προσέγγιση (δηλ. χωρίς περιορισμούς στα μοντέλα των συνιστωσών), όμως με την άμεση προσέγγιση τα οφέλη καλύπτουν περισσότερους τομείς και ορίζοντες πρόβλεψης.

1. Introduction

Up-to-date information on the state of the economy is crucial for both economic policy making and private financial decision making. As national accounts data are published with a delay vis-à-vis the reference quarter, reliable short-term forecasts for aggregate and sectoral activity could offer valuable insights into future economic conditions. Modern econometric techniques exploit the richness of timely information in large databases of economic and financial indicators of different frequencies, in the construction of short-term macroeconomic forecasts.

This work relates to two main strands of the forecasting literature. The first strand concerns techniques for summarising the information in large sets of predictors, such as common factors and forecast combinations. The application of forecast combination techniques and the use of common factors in the forecasting models are found to substantially improve on the accuracy of univariate autoregressive forecasts (e.g. Artis et al. 2005 for the UK; Giannone et al. 2008 and Stock and Watson 2002a for the US; Stock and Watson 2004 for OECD countries). The second strand relates to the level of disaggregation at which the forecasts are computed, and typically distinguishes between direct and bottom-up forecasting approaches. Lütkepohl (2010) provides theoretical results on the relative efficiencies of aggregate and disaggregate forecasts under some assumptions and offers some guidelines for applied work. Theoretically, forecasting the disaggregate components using a multivariate model is at least as efficient in terms of mean squared error as directly forecasting the aggregate. However, in practice, issues such as specification and estimation uncertainty, non-linear transformations of the variable of interest and time-varying aggregation weights lead to departures from the theoretical assumptions, and empirical findings could deviate from theoretical results. For example, computing bottom-up forecasts for the aggregate by modelling the disaggregates using a high dimensional multivariate model or a large number of disaggregate single equation models may result in higher estimation uncertainly than directly modelling and forecasting the aggregate variable. Applications include aggregate inflation measures and their sub-indices, GDP and its supply and/or demand components as well as aggregate output, inflation, unemployment and money stock series for blocs of countries (e.g. the euro area) and their country-specific counterparts (e.g. Barhoumi et al. 2012; Bermingham and D'Agostino 2014; Brüggemann and Lütkepohl 2013; Foroni and Marcellino 2014; Hendry and Hubrich 2011; Hubrich 2005; Marcellino et al. 2003).

Empirical applications use single equation dynamic models for an aggregate (e.g. GDP growth, inflation) and similarly for its components, or simple Vector Autoregressions (VARs) that jointly model one variable of interest (e.g. an aggregate or a component) and few predictors. The literature on the forecasting performance of systems of equations for jointly modelling the components of an aggregate relates mostly to inflation sub-indices. In a simulation exercise Hendry and Hubrich (2011) demonstrate that when disaggregates are interrelated, forecasting an aggregate variable using a VAR model for the disaggregates is superior to directly forecasting the aggregate with an autoregressive model (AR) or summing forecasts for the disaggregates from AR models. However, the empirical results in Hendry and Hubrich (2011) for the US and in Hubrich (2005) for the euro area show that bottom-up forecasts based on VAR models for inflation sub-indices are outperformed by aggregate inflation forecasts computed directly, possibly due to high estimation uncertainty associated with VAR models. Moreover, Bermingham and D'Agostino (2014) use large Bayesian VARs with parameter restrictions to model US and euro area inflation sub-indices and subsequently construct forecasts for aggregate inflation. For the US, they find some gains over single equation models for short horizons; for the euro area, they conclude that AR models yield the best results due to absence of strong commonality between sub-indices. Other works using system methods, for example VARs, Bayesian VARs, Factor Augmented VARs, Factor Augmented Error Correction models, focus on forecasting output growth together with other macroeconomic aggregates such as inflation, interest rate, employment or unemployment (e.g. Banerjee et al. 2014; Koop 2013; Marcellino et al. 2003; Stock and Watson 2002a).

The aim of this paper is to apply single equation dynamic models in the construction of short-term forecasts for the growth rate of GDP and its production-side components in Cyprus. The production-side components of GDP consist of the Gross Value Added (GVA) in 10 sectors of economic activity as well as import duties plus Value Added Tax (VAT), thus completely covering the supply-side of the quarterly national accounts published by the Statistical Service of Cyprus. Currently, local policy makers and international organisations publish forecasts for macroeconomic aggregates in Cyprus as well as projections for the demand-side components of GDP. This work aspires to expand the set of available forecasts for Cyprus by offering growth forecasts for sectors of economic activity that are consistent with forecasts for aggregate activity. The availability of sectoral activity forecasts can provide additional information to policy makers, investors and business on the drivers of future growth, especially as sectoral activity cycles could precede or follow fluctuations in aggregate activity, depending on the sector. Analysing the outlook at a sectoral level could unveil domestic or external factors which influence sectoral growth, structural strengths/weakness in sectors and vulnerabilities of specific sectors to shocks. Sectoral forecasts can therefore assist policy makers in formulating informed economic policies and facilitate private agents in their economic decision-making and planning. Another contribution of the paper is that the forecasts are computed using a large dataset of over 300 domestic and foreign predictors together with techniques such as common factors and forecast combinations for summarising the information content in the dataset. We compute forecasts using a bottom-up and a direct approach. In the bottom-up approach we construct unconstrained sectoral growth forecasts that are aggregated to obtain GDP growth forecasts. The direct approach amounts to forecasting GDP growth directly and obtaining a set of component forecasts by imposing constraints. The forecasting performance of the aggregate and component forecasts computed under each approach is evaluated. It is also investigated whether the use of pre-selected indicators as opposed to the full dataset improves the forecasting performance.

Empirical evidence on the forecasting performance of aggregate forecasts computed directly and bottom-up forecasts computed by aggregating predictions for the disaggregate components is mixed. Hahn and Skudelny (2008) compute euro area GDP growth forecasts using the bottom-up approach from the production side together with sector-specific bridge equations that vary across the forecast cycle. The authors assess two alternative bottom-up approaches depending on whether the value added for the services sector is forecasted directly or via its sub-components. They find marginal differences in the performance of the two approaches. Their results also suggest that the importance of individual predictors varies substantially over the forecast cycle, with survey data being more valuable at earlier stages of the forecast cycle and hard data being more useful at later stages of the cycle. Barhoumi et al. (2012) forecast French GDP growth indirectly using the bottom-up approach from both the supply side and the demand side, using component-specific bridge models. Their results suggest that forecasting GDP growth from the supply side is superior to following a demand-side bottom-up approach; the finding is likely driven by the availability of more relevant indicators for sectors of economic activity than for expenditure components. Drechsel and Scheufele (2013) estimate German GDP growth using the direct approach as well as the bottom-up approach, via both the supply and demand sides. They employ mixed-data sampling regressions together with model averaging techniques. Their findings suggest that aggregating sector-specific forecasts results in limited forecasting gains compared to forecasting GDP growth directly, whereas both approaches outperform forecasts produced from the demand side. Foroni and Marcellino (2014) employ a large dataset of monthly indicators and different modelling approaches (i.e. bridge equations, mixed data sampling and mixed frequency VAR models) for nowcasting both the expenditure and production GDP components. They find gains over the autoregressive benchmark when information from monthly indicators is incorporated in forecasting models, particularly in the case of industry and financial services for which there are available predictors. Their results from directly forecasting GDP growth are generally superior, although a bottom-up approach using factor models or bridge equations for the production side components is also promising, and they conclude that there is scope for forecasting the components to gain better understanding of the aggregate.

Our results show that the use of macroeconomic and financial predictors improves on the accuracy of the naïve forecasts for most production-side components and the aggregate, under both the direct and bottom-up approaches. GDP growth forecasts from the direct approach are somewhat superior to those from the bottom-up approach. Both approaches result in forecast gains in industry, construction, trade, financial activities and duties. In the sector of professional services gains are limited for both constrained and unconstrained forecasts. In the sectors of agriculture and public administration, education and health, neither the unconstrained models nor the constrained sectoral models significantly improve on the naïve benchmark. Compared to the unconstrained forecasts, gains attained through constrained forecasts are slightly lower, but more widespread across components and horizons.

The structure of the paper is as follows. Section 2 describes the methodology. Section 3 presents the data and provides some results on the estimation of factors. Section 4 examines the forecasting performance of growth forecasts for the supply-side components and compares the accuracy of GDP growth forecasts from the direct and bottom-up approaches. Section 5 discusses the construction and performance of constrained component forecasts as well as the stability of the forecasting performance of the methods considered. Section 6 concludes.

2. Methodology

The methodology is based on the following single equation models:

(a) autoregressive (AR) models, i.e. they include only lagged values of the dependent variable;

(b) autoregressive distributed lag (ADL) models, i.e. they include lagged values of the dependent variable, and lags and leads–if available–of economic/financial indicators;

(c) factor-augmented AR (FAR) and factor-augmented ADL (FADL) models, i.e. AR and ADL models, as described above, that also include lagged values of common factors and leads of leading indicators used in factor estimation.

The ADL and factor-augmented models allow us to assess forecasting gains resulting from utilising information from different macroeconomic and financial predictors beyond that contained in the history of the variable of interest.

Factor models summarise the information from a large number of economic/financial time series by a small number of estimated indices known as common factors. Thus, the dynamics of a dataset of many economic time series can be driven by a small number of common shocks and a set of idiosyncratic components, i.e. one series-specific shock for each variable in the dataset. In the analysis that follows, the factors are extracted from a dataset of economic activity and labour market indicators, thus the estimated factors can be viewed as representing aspects of the real economy. Real economy factors alone or together with other aspects of the economy (e.g. prices, financial indicators, economic sentiment) can affect future sectoral or aggregate activity. The factors are estimated using the principal components method and are subsequently used in the factor-augmented forecasting models (see e.g. Stock and Watson 2002a, 2002b).

Apart from the large number of series relating to the real economy, the dataset employed contains a large number of candidate predictors which cover other aspects of the economy, such as stock market indicators, interest rates, exchange rates, consumer price indices, international commodity prices, economic sentiment indicators, loans and deposits. Such series are published on a monthly basis and well before the publication of the national accounts. The monthly values of these series, known as monthly leads, can be used in estimation and forecasting as they provide up-to-date information on economic conditions. Monthly leads could cover one to three months (i.e. the whole quarter) following the reference quarter of the most recently available national accounts data.[1]

2.1 Models

In the forecasting models the variable of interest is expressed in annualised percentage changes, i.e. $y_{t+h}^{h} = (400/h)(\ln Z_{t+h} - \ln Z_t)$, observed for quarters $t = 1, \dots, T$; h denotes the forecast horizon in quarters and Z_t denotes the level of GDP, sectoral GVA, or import duties plus VAT. The h-step ahead regression model used for computing the forecasts for $h = 1, \dots, 8$ can be given by univariate, ADL or factor-augmented models.

The univariate models are given by

$$y_{t+h}^{h} = \alpha + \sum_{i=0}^{q} \beta_i y_{t-i} + \eta_{t+h}^{h} \quad (1)$$

where η_{t+h}^{h} is the error term. Equation (1) gives the AR model of order q. For $\beta_i = 0$, equation (1) reduces to the RW model for the log-level, which is a constant growth model.

The extensive dataset employed contains a large number of candidate predictors that are published on a monthly basis and well before the publication of the national accounts. Let x_t denote a predictor in quarterly frequency. In order to utilise the information in the monthly leads relating to predictor x_t we extend the simple ADL model as follows

$$y_{t+h}^{h} = a + \sum_{i=0}^{q} b_i y_{t-i} + \sum_{i=0}^{p} c_i x_{t-i} + d' x_{t+1}^{L} + e_{t+h}^{h} \quad (2)$$

where x_{t+1}^{L} is a scalar or vector of leads, depending on data availability, i.e. leading information can cover the first month in quarter $t + 1$, the first two months in quarter $t + 1$, or all the months in quarter $t + 1$.[2, 3] The model in (2) is an ADL model with monthly or quarterly

[1] For some candidate predictor series such as stock market indicators, exchange rates and business and consumer survey variables, quarterly leads (up to one quarter ahead) might be available.

[2] Depending on data availability, $x_{t+1}^{L} = x_{t+1}^{M1}$, $x_{t+1}^{L} = [x_{t+1}^{M1} \quad x_{t+1}^{M2}]'$ or $x_{t+1}^{L} = x_{t+1}$, and x_{t+1}^{M1} (x_{t+1}^{M2}) denotes the monthly values of quarterly series x_t covering the first (second) month in quarter $t + 1$; x_{t+1} denotes the quarterly value leading variable x_t by one quarter.

[3] Examples of variables for which one or two monthly leads are available include registered unemployed, unemployment, registration of motor vehicles, tourist arrivals, domestic interest rates,

leads and constitutes a special case of the mixed data sampling regression in Andreou et al. (2013) that includes mixed frequencies in the lags of the predictors.

The estimated quarterly factors are used to extend simple dynamic models, such as the AR and ADL that are subsequently used for forecasting; the resulting models are known as factor-augmented AR (FAR) and factor-augmented ADL (FADL) models given by (3a) and (3b), respectively,

$$y_{t+h}^{h} = \gamma + \sum_{i=0}^{q} \xi_i y_{t-i} + \sum_{i=0}^{l} \phi_i \hat{f}_{t-i} + \theta' \, r_{t+1}^{L} + \upsilon_{t+h}^{h} \tag{3a}$$

$$y_{t+h}^{h} = \zeta + \sum_{i=0}^{q} \kappa_i y_{t-i} + \sum_{i=0}^{p} \lambda_i x_{t-i} + \mu' x_{t+1}^{L}$$

$$+ \sum_{i=0}^{l} \rho_i \hat{f}_{t-i} + \pi' r_{t+1}^{L} + \varepsilon_{t+h}^{h} \, . \tag{3b}$$

$\hat{f}_t$ is one of the estimated factors summarising a large dataset of real economy series, and r_{t+1}^{L} is a scalar or vector of leads associated with variables used in the construction of factors and is defined similarly to x_{t+1}^{L}. In (3b) x_t is a candidate predictor other than the real economy series used in factor estimation, and x_{t+1}^{L} denotes its leads as in model (2).

The estimated factors $\hat{f}_t$ which are obtained by application of principal components analysis on a large panel of real economy series prior to the estimation of the forecasting models in (3a) and (3b) constitute estimated regressors.[4] Stock and Watson (2002b) show that the factor estimator based on principal components analysis is consistent, and feasible forecasts computed from the factor-augmented regression are asymptotically efficient. Bai and Ng (2006) show that the limiting distribution of estimators in factor-augmented regressions is normal and construct confidence intervals for parameters and forecasts. The investigation of finite sample performance in Stock and Watson (2002b) revealed that for sample sizes typically encountered in empirical work, the forecasting performance of factor-augmented regressions is fairly robust to moderate serial and spatial correlation, fairly large shifts in factor loadings and inclusion of irrelevant predictors in the panel. However, when all of the above misspecifications co-occur the forecast accuracy is considerably reduced.

The estimation of the parameters and the selection of the number of lags in models (1) to (3b) are carried out in a pseudo out-of-sample setup using recursive OLS and recursive determination of lag length based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).[5] The choice of the number of lags for predictor x_t and factor $\hat{f}_t$ is between one and four; for the dependent variable y_t lags vary between zero and

loans and deposits. Examples of variables for which three monthly leads (i.e. a quarter) are available include business and consumer survey series, domestic consumer price indices, European interest rates and spreads, stock market indicators, exchange rates and international commodity prices.

[4] For details about the factor model and estimation see Appendix (A1).

[5] Factors are estimated recursively by principal components analysis, i.e. at each iteration prior to the estimation of OLS regressions principal components analysis is applied to obtain estimates for the factors.

four. The forecast constructed in t, for period $t+h$, uses data up to t and monthly leads if available; thus no additional projections for predictors are required, unlike the case of iterated forecasts (see e.g. Stock and Watson 2004, 2008).

The h-quarter ahead forecast for y_{t+h}^{h} computed in period t is given by $\hat{y}_{t+h}^{h}$. First, the models are estimated over the period $t = 1,2,\dots,T_1$ and the first pseudo out-of-sample forecast, $\hat{y}_{T_1+h}^{h}$, is computed in quarter $t = T_1$. The recursive procedure requires increasing the sample size by one observation, re-estimating the models over the period $t = 1,2,\dots,T_1+1$ and computing the second pseudo out-of-sample forecast, $\hat{y}_{T_1+1+h}^{h}$, in quarter $t = T_1$+1. The procedure is repeated up to period $T-h$, so that the last pseudo out-of-sample forecast, $\hat{y}_{T}^{h}$, is computed in quarter $t = T-h$.

The forecasting performance of each model for horizon h is evaluated using the Mean Squared Forecast Error (MSFE) given by

$$MSFE = \frac{1}{T-h-T_1+1}\sum_{t=T_1}^{T-h}(y_{t+h}^{h} - \hat{y}_{t+h}^{h})^2. \tag{4}$$

2.2 Forecast combinations

The numerous predictors in the dataset in combination with the factors and leads, allow us to estimate a large number of different models and to obtain many alternative forecasts for the variables of interest. The large number of forecasts can be further exploited by constructing combinations of forecasts.

There is ample literature that suggests that forecast combinations can provide more accurate forecasts by using evidence from all the models considered rather than relying on a specific model (e.g. Stock and Watson 2004, 2008, Timmermann 2006). Forecast combinations reduce the uncertainty resulting from the specification of individual models due to different set of predictors, lag structures and modelling approaches. Also, forecast combinations can be more robust to structural breaks than individual forecasts.

There are different methods to construct forecast combinations depending on how the forecast weights are formed. Given M models and associated forecasts, a combination forecast denoted by $\hat{F}_{t+h}^{h}$, is the weighted average of individual forecasts, with fixed or time-varying weights,

$$\hat{F}_{t+h}^{h} = \sum_{i=1}^{M} w_{i,t}\, \hat{y}_{i,t+h}^{h} \tag{5}$$

where $\hat{y}_{i,t+h}^{h}$ is the h −step ahead forecast from model i computed in period t and $w_{i,t}$ is the weight assigned to that forecast. In general the weight ($w_{i,t}$) depends on the historical forecasting performance of model i, however $w_{i,t}$ can be fixed, leading to simple forecast combinations such as the mean ($w_{i,t} = 1/M$), the median or some type of trimmed mean. In cases in which $w_{i,t}$ depends on a model's past forecasting performance the resulting combination forecasts are known as discounted MSFE forecasts (Stock and Watson 2004). In particular, the weights can be inversely proportional to the discounted MSFE (or the square of the discounted MSFE) of the individual models, i.e.

$$w_{i,t} = \frac{\epsilon_{i,t}}{\sum_{j=1}^{M} \epsilon_{j,t}} \text{, or,} \tag{6}$$

$$w_{i,t} = \frac{(\epsilon_{i,t})^2}{\sum_{j=1}^{M} (\epsilon_{j,t})^2} \tag{7}$$

where $\epsilon_{i,t} = \left[\sum_{s=T_1}^{t-h} \delta^{t-h-s} (y_{s+h}^h - \hat{y}_{i,s+h}^h)^2\right]^{-1}$;

δ is the discount factor so that forecast errors made in the distant past are of smaller importance. Larger weights are assigned to forecasts from models with lower MSFE (i.e. better historical forecasting performance).

The performance of forecast combination methods is evaluated using the MSFE statistic in equation (4) where the individual model forecast, $\hat{y}_{t+h}^h$, is replaced by the combination forecast $\hat{F}_{t+h}^h$.

In the empirical analysis that follows, the forecasts, $\hat{y}_{i,t+h}^h$ included in the forecast combinations are those computed from all ADL and factor-augmented models (FAR and FADL) with the optimal lag order determined by the AIC and BIC. Thus, forecast combinations can be used to assess the potential usefulness of information in macroeconomic and financial indicators, in addition to information contained in the history of the variable of interest, for forecasting aggregate and sectoral growth rates.

3. Data

The dataset used for estimation and forecasting covers the period 1995Q1 – 2016Q2 and contains about 330 variables that represent many aspects of the domestic economy and the external economic environment. Domestic data include national accounts variables, short-term economic activity indicators (e.g. volume indices of retail trade and manufacturing, cement sales, building permits, tourist arrivals), labour market series (e.g. employment, unemployment, vacancies), fiscal data and public debt, banking sector data (loans, deposits, interest rates), price indices, Cyprus Stock Exchange indices and survey data on business and consumer confidence. Foreign/international data are comprised of euro exchange rates to different currencies (e.g. US dollar, British pound, Russian rouble), foreign activity and labour market indicators, European interest rates and spreads, foreign price indices and international commodity prices (e.g. oil, gold, wheat), stock market indicators and European economic confidence/sentiment indicators. All series are adjusted for seasonality and transformed into stationary by differencing (the levels or the logarithm of the levels) if needed.[6, 7, 8]

The focus of this paper is on the construction of forecasts for the growth rate of GVA (in constant prices) in the sectors of economic activity presented in the quarterly national accounts, and for the growth rate of import duties plus VAT. Also, projections for GDP growth are computed via the predictions for the production-side components of national accounts as well as by forecasting the aggregate directly. More specifically, forecasts are constructed for the growth rate of GVA in the 10 sectors listed below:

1. Agriculture, forestry and fishing (NACE code A);
2. Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities (NACE codes B, C, D, E);
3. Construction (NACE code F);
4. Wholesale and retail trade; repair of motor vehicles and motorcycles; transport, storage and communication; accommodation and food service activities (NACE codes G, H, I);
5. Information and communication (NACE code J);
6. Financial and insurance activities (NACE code K);
7. Real estate activities (NACE code L);
8. Professional, scientific and technical activities; administrative and support service activities (NACE codes M, N);
9. Public administration and defence; compulsory social security; education; human health and social work activities (NACE codes O, P, Q);
10. Arts, entertainment and recreation; other service activities; activities of households as employers; undifferentiated goods and services producing activities of households for own use (NACE codes R, S, T).

Some statistics on the variables of interest are shown in Table 1; the statistics are presented for the full sample period as well as for two sub-samples covering the periods before and after 2009, i.e. before and after the international financial crisis.[9] A statistically significant break in the mean of GDP growth and the growth rate of nine components was found, with estimated break dates lying in the period 2008 – 2012.[10] The split in the sample shown in Table 1 follows the estimated break date for GDP growth.

[6] Table A1 (Appendix) shows the number of series in dataset by category.

[7] Data are obtained from different sources, such as the Statistical Service of Cyprus, the Central Bank of Cyprus, the Cyprus Stock Exchange, the Department of Lands and Surveys, Eurostat, the European Commission (DG-ECFIN), the European Central Bank, Datastream and Global Financial Data.

[8] A detailed list of the variables in the dataset along with their transformations is available upon request.

[9] Figure A1 (Appendix) presents GDP growth over time vis-à-vis the growth rates of the 11 GDP components.

[10] The results are based on supremum Wald and Likelihood Ratio tests for a structural break at an unknown break date (e.g. Andrews 1993).

TABLE 1

GDP and production-side components

		GDP	GVA: Agriculture, forestry and fishing	GVA: Industry	GVA: Construction	GVA: Trade, transport, accommodation and food services	GVA: Information and communication	GVA: Financial and insurance activities	GVA: Real estate activities	GVA: Professional and administrative services	GVA: Public administration, education and health services	GVA: Other services	Import duties plus VAT
1996Q1 – 2016Q2													
Quarter-on-quarter changes (%)	Mean	0.5	-0.1	-0.2	-0.2	0.5	1.9	1.4	0.8	0.9	0.5	0.7	0.5
	St. Dev.	1.0	9.0	1.7	5.4	1.6	2.9	1.8	0.8	1.4	0.7	1.9	1.6
Year-on-year changes (%)	Mean	2.1	-1.3	-0.6	-0.6	2.0	8.1	5.9	3.2	3.7	2.1	2.8	2.1
	St. Dev.	3.1	11.3	4.9	12.1	4.5	8.9	6.7	2.3	4.3	2.3	6.0	3.1
Component share to GDP	Mean	_	2.7	8.8	7.0	22.6	2.8	6.6	7.4	7.3	18.5	3.6	12.6
	St. Dev.	_	0.9	1.7	1.6	0.6	0.7	1.5	0.7	0.6	0.7	0.3	0.1
1996Q1 – 2008Q4													
Quarter-on-quarter changes (%)	Mean	1.0	-0.2	0.3	1.3	0.9	2.5	2.2	0.8	1.3	0.8	1.4	1.0
	St. Dev.	0.7	7.9	1.1	5.2	1.5	3.0	1.4	0.2	1.2	0.5	1.4	1.5
Year-on-year changes (%)	Mean	3.9	-1.7	1.2	5.6	3.7	11.4	9.0	3.3	5.2	3.1	5.5	3.9
	St. Dev.	1.4	10.1	2.2	8.1	3.9	8.8	5.6	0.8	3.5	1.4	3.9	1.4
Component share to GDP	Mean	_	3.2	9.8	7.6	22.6	2.5	5.7	7.0	7.0	18.4	3.4	12.6
	St. Dev.	_	0.6	1.0	1.2	0.7	0.7	0.9	0.2	0.3	0.7	0.1	0.1
2009Q1 – 2016Q2													
Quarter-on-quarter changes (%)	Mean	-0.2	0.1	-0.9	-2.7	-0.1	0.6	-0.1	0.7	0.3	0.1	-0.5	-0.2
	St. Dev.	0.9	10.6	2.2	4.8	1.3	2.1	1.3	1.3	1.5	0.7	2.2	1.5
Year-on-year changes (%)	Mean	-1.0	-0.6	-3.9	-11.4	-1.0	2.4	0.7	2.9	1.2	0.4	-1.8	-1.0
	St. Dev.	2.8	13.0	6.4	10.2	3.8	5.5	4.9	3.6	4.5	2.5	6.2	2.7
Component share to GDP	Mean	_	1.8	6.9	6.0	22.5	3.4	8.2	7.9	8.0	18.6	4.0	12.6
	St. Dev.	_	0.1	0.8	1.8	0.3	0.4	0.5	0.8	0.4	0.8	0.2	0.1

The largest sector in terms of value added contribution to GDP is trade, transport, accommodation and food services followed by public administration, education and health services. Information and communication activities, and financial and insurance services have been the fastest growing sectors over the period 1996 – 2016, while the construction sector has registered the highest volatility in activity growth over the same period. After 2008, output growth in all sectors, except agriculture and real estate activities, slowed down significantly. Over the period 2009 – 2016, the contribution of services to GDP increased, while the shares of the primary and secondary sectors declined.

To take into account the presence of breaks in the variables of interest we include dummy variables in the models described in section 2.1 and consider forecast combinations as opposed to forecasts obtained using individual predictors. The stability of the forecasting performance is briefly explored in section 5.3.

Next, some results from principal components analysis applied to a panel of 159 real economy variables over the period 1995Q1 – 2016Q2 are discussed to give an idea of the estimated factors that are included as predictors in the forecasting models; these factors summarise information about domestic and foreign real economic conditions.[11]

Table 2 presents the marginal contribution of each factor (i.e. principal component) in explaining the total variance in the 159 series. This contribution decreases substantially after the second factor. The first factor explains 20% of the cross-section variation in the data, while the first and second factor jointly contribute about 28% to the total variance; the first 12 factors account for 59% of variance in the dataset. Table 2 also shows three alternative information criteria (ICP1, ICP2, ICP3) for the choice of the number of factors (see Bai and Ng 2002). The number of factors estimated by each criterion is the one that corresponds to the smallest value of the criterion. The first two criteria suggest a small number of factors, namely two, whereas the third criterion estimates nine factors.

Figure 1 shows how each one of the 12 factors relates to the different categories of variables in the dataset. Loosely speaking, Figure 1 can be interpreted as how the R^2's from regressions of factors on each of the series in the dataset (i.e. the percentage of the variation in each factor explained by each variable) are distributed among the various categories of variables. For example, the first two factors correlate mostly with foreign real activity indicators, while the third one loads mainly on domestic activity and labour market variables; the eighth factor represents, to a great extent, domestic activity series.[12]

[11] The dataset is comprised of variables under the following categories shown in Table A1 (Appendix): domestic activity, excluding GDP (e.g. industrial production indices, volume index of retail trade, building permits, cement sales, electricity production and consumption, registration of motor vehicles, tourist arrivals), domestic labour market (e.g. employment, registered unemployed, unemployment rate, vacancies), foreign activity and labour market (e.g. industrial production and unemployment rate for the EU, the euro area and specific countries with which Cyprus has strong trade links).

[12] In the pseudo out-of-sample forecasting exercises that follow, factors are estimated at each iteration; only one factor at a time is included in each FAR or FADL model. The first eight factors are used in the forecasting models at each iteration.

TABLE 2

Estimation of factors

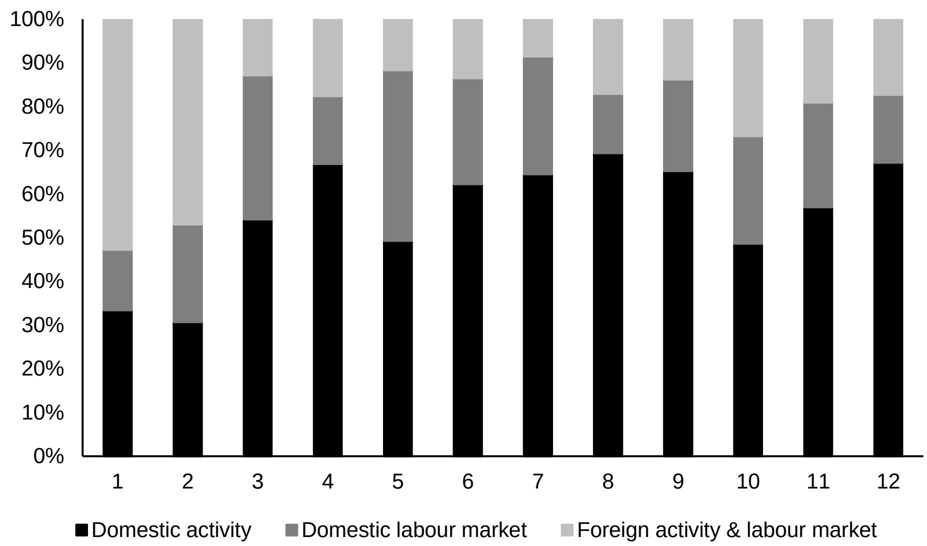
Number of factors	Marginal contribution to total variance (%)	Information criteria (ICP) for selecting the number of factors		
		ICP1	ICP2	ICP3
0	_	-0.0118	-0.0118	-0.0118
1	20.0	-0.1627	-0.1549	-0.1829
2	7.8	-0.1926	-0.1771	-0.2330
3	4.7	-0.1870	-0.1638	-0.2476
4	4.3	-0.1801	-0.1492	-0.2610
5	3.6	-0.1665	-0.1279	-0.2676
6	3.5	-0.1548	-0.1084	-0.2760
7	3.0	-0.1382	-0.0840	-0.2796
8	2.8	-0.1190	-0.0571	-0.2807
9	2.6	-0.0990	-0.0295	-0.2809
10	2.4	-0.0784	-0.0010	-0.2805
11	2.3	-0.0569	0.0281	-0.2792
12	2.0	-0.0326	0.0602	-0.2751
	Cumulative contribution (%)	Number of factors estimated by ICP		
	59.0	2	2	9

Notes: The number of series in the balanced panel is 159 and the number of time periods is 85 after transforming the series to induce stationarity. The sum of squared residuals (idiosyncratic components) is 5482 and the total variance of the dataset is 13356.

The percentages are derived from the estimated eigenvalues of the data matrix.

FIGURE 1

Relation between factors and groups of variables in the dataset



4. Forecasting performance

The single equation models described in section 2 are employed for forecasting the growth rates of the production-side components of GDP i.e. GVA (constant prices) in 10 sectors of economic activity, and import duties plus VAT. Forecasts for GDP growth are also computed. The extensive dataset of domestic and foreign predictors used for estimation and forecasting, results in a large number of ADL and factor-augmented (FAR and FADL) models and, therefore, forecasts for each variable of interest. Thus, we consider forecast combinations of individual model forecasts as the stability of the forecasting performance of models based on individual predictors could suffer (e.g. Stock and Watson 2003, 2004).

In the forecasting exercise we apply the following combination methods:

(a) Simple methods, namely the median, mean and trimmed mean, i.e. the mean after discarding the highest and lowest 5% of the distribution of individual model forecasts.

(b) Methods based on models' past forecasting performance using the discounted MSFE and squared MSFE with weights given by equations (6) and (7), respectively, and discount factor $\delta = 0.9, 0.95, 1$.

The data used for recursive estimation and pseudo out-of-sample forecasting exercise cover the period 1995Q1 – 2016Q2. The first estimation period consists of 24 observations; the first pseudo out-of-sample forecast is constructed in quarter 2002Q1 for a horizon of one quarter ahead; as the horizon increases the date on which the first forecast is constructed is shifted forward by one quarter.[13]

4.1 GVA growth: sectoral forecasts

Table 3 presents the results of the forecasting exercise for the growth rate of all components that are presented in the production side of the quarterly national accounts. The forecasts are computed from the following models/methods:

(a) univariate models;

(b) combinations of ADL and factor-augmented model forecasts estimated using all predictors in the dataset;

(c) forecast combinations of ADL and factor-augmented model forecasts estimated using a set of pre-selected predictors that are significantly correlated with the variable to be forecasted.

The use of a large number of indicators for forecasting has spurred research on the effects of pre-selecting predictors on forecasting performance (e.g. Ng 2013).[14] Boivin and Ng (2006) find that factors extracted from a set of 40 pre-screened indicators do not worsen the the forecasting performance vis-à-vis the case that the full set of 147 series is used for factor

[13] For each horizon $h + 4$ observations are lost due to the transformation of the dependent variable and the number of lags in the models. Thus, in the notation of equation (4), T_1 is the date that corresponds observation numbered $28 + h$, i.e. 2002Q1 for $h = 1$, 2002Q2 for $h = 2$ and so on. For combination forecasts based on past forecasting performance the first pseudo out-of-sample forecast is constructed in 2002Q2 (for $h = 1$).

[14] Preliminary testing for the selection of a sub-set of regressors from a larger set of variables is known to distort subsequent statistical inference and introduce biases (e.g. Griffiths et al. 1993, Ch. 10). Moreover, evidence in favour of in-sample predictability might not necessarily translate into good out-of-sample forecasting performance, although Inoue and Kilian (2004) explore explanations for this discord arising in empirical analyses.

estimation. They conclude that it is not simply the number of series in the panel that determines estimation and forecasting efficiency but also the information quality of the panel for factor estimates. The benefits of pre-selecting predictors on forecast accuracy are documented in a number of empirical studies (e.g. Bai and Ng 2008 for US inflation; Bullingan et al. 2015 for Italian GDP growth and its expenditure components; Caggiano et al. 2011 for GDP growth in large European countries and the euro area; Girardi et al. 2017 for GDP growth in the euro area) and provide the motivation for considering subsets of the full dataset pre-selected specifically for each component.[15]

Table 3 presents the square root of MSFE (RMSFE) of the different methods relative to that of the random walk benchmark each component. The entries in bold indicate that the performance of the model/method is superior vis-à-vis the naïve benchmark and the difference is statistically significant.

Not all sectors are associated with significant gains over the random walk model. For the sectors of agriculture and public administration, education and health services, information from macroeconomic time series does not increase the accuracy of the forecasts. For industry, construction and trade, the improvement in the predictive accuracy due to the use of economic and financial predictors is significant only for short horizons (up to four quarters ahead). For construction, the simple AR(4) model leads to similar gains as combination forecasts. In forecasting activity growth in the abovementioned sectors no noticeable error reduction occurs from the use of pre-selected predictors.

For the sectors of professional and administrative services as well as other services, macroeconomic and financial predictors significantly enhance the forecasting performance only for one-quarter ahead forecasts. For the sector of information and communication, some gains are achieved by incorporating information from other predictors in the forecasting models, but the error reduction is significant only for two-quarter ahead forecasts; nevertheless, the AR(1) model seems to be associated with the lowest errors (i.e. significant MSFE reduction relative to the benchmark for horizons of two to five quarters).

[15] The set of pre-selected predictors is determined by the statistical significance (at 10% level) of the in-sample correlation coefficient between the growth rate of each variable of interest and each predictor (current and lagged terms) in the dataset. Recursive correlation estimates reveal that the numbers of pre-selected predictors from the different categories (e.g. domestic and foreign real economy series, other domestic series, other foreign series) increase considerably after 2008 and remain high up to the end of the sample period. Alternative pre-selection techniques (e.g. Ng 2013), leading to sets of selected predictors different than those employed in this paper, could affect the forecasting performance differently; such techniques could be explored in future work.

TABLE 3

RMSFE relative to random walk, growth by component

Forecast horizon (quarters)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Agriculture, forestry and fishing, GVA								
Random walk benchmark, RMSFE	8.83	9.16	9.12	10.77	11.00	11.17	11.30	11.72
AR(AIC)	0.97	1.01	1.00	1.06	1.06	1.06	1.04	1.01
AR(BIC)	1.00	1.00	1.00	1.04	1.00	1.00	1.04	1.00
AR(1)	0.96	0.98	0.94	0.95	1.00	0.99	1.00	1.00
AR(4)	0.97	0.96	1.01	1.06	1.06	1.06	1.03	1.03
Forecast combinations, all predictors								
Median	1.03	1.00	1.07	1.13	1.07	1.09	1.07	1.04
Mean	1.02	1.02	1.10	1.15	1.10	1.10	1.09	1.06
Trimmed mean (5% trimming)	1.02	1.01	1.10	1.14	1.09	1.10	1.08	1.06
Discounted MSFE (0.90)	1.02	1.01	1.12	1.14	1.10	1.10	1.09	1.07
Discounted MSFE (0.95)	1.02	1.01	1.12	1.14	1.10	1.10	1.09	1.07
Discounted MSFE (1.00)	1.02	1.01	1.12	1.15	1.10	1.10	1.09	1.07
Squared discounted MSFE (0.90)	1.03	1.01	1.15	1.14	1.10	1.10	1.09	1.08
Squared discounted MSFE (0.95)	1.03	1.01	1.15	1.14	1.10	1.10	1.09	1.08
Squared discounted MSFE (1.00)	1.03	1.01	1.15	1.15	1.10	1.09	1.09	1.08
Forecast combinations, pre-selected predictors								
Median	1.02	0.99	1.05	1.13	1.08	1.08	1.08	1.05
Mean	1.02	1.01	1.07	1.15	1.10	1.08	1.09	1.07
Trimmed mean (5% trimming)	1.02	1.00	1.06	1.14	1.09	1.08	1.08	1.06
Discounted MSFE (0.90)	1.02	1.01	1.07	1.15	1.10	1.09	1.09	1.07
Discounted MSFE (0.95)	1.02	1.01	1.07	1.15	1.10	1.09	1.09	1.07
Discounted MSFE (1.00)	1.02	1.01	1.07	1.15	1.10	1.09	1.09	1.07
Squared discounted MSFE (0.90)	1.02	1.00	1.07	1.14	1.10	1.10	1.09	1.08
Squared discounted MSFE (0.95)	1.02	1.00	1.07	1.14	1.10	1.09	1.09	1.08
Squared discounted MSFE (1.00)	1.02	1.00	1.07	1.15	1.10	1.09	1.09	1.08
2. Industry, GVA								
Random walk benchmark, RMSFE	1.42	2.55	3.69	4.90	5.02	5.04	5.24	5.46
AR(AIC)	**0.92**	**0.90**	**0.95**	0.95	1.00	1.00	1.02	1.03
AR(BIC)	**0.91**	**0.92**	0.96	**0.98**	1.00	1.00	1.00	1.00
AR(1)	**0.90**	**0.90**	**0.91**	**0.92**	0.96	0.99	0.99	1.01
AR(4)	**0.93**	**0.89**	**0.91**	0.95	1.00	1.04	1.05	1.07
Forecast combinations, all predictors								
Median	**0.90**	**0.87**	**0.90**	0.93	0.96	0.98	0.99	1.00
Mean	**0.90**	**0.86**	**0.89**	0.93	0.95	0.98	0.99	1.01
Trimmed mean (5% trimming)	**0.90**	**0.86**	**0.90**	0.93	0.96	0.98	0.98	1.00
Discounted MSFE (0.90)	**0.89**	**0.85**	**0.89**	0.92	0.94	0.97	0.99	1.01
Discounted MSFE (0.95)	**0.89**	**0.86**	**0.89**	0.92	0.94	0.97	0.99	1.01
Discounted MSFE (1.00)	**0.89**	**0.86**	**0.89**	0.92	0.95	0.97	0.99	1.01
Squared discounted MSFE (0.90)	**0.89**	**0.85**	0.89	0.92	0.94	0.97	0.99	1.02
Squared discounted MSFE (0.95)	**0.89**	**0.85**	0.89	0.92	0.94	0.97	0.99	1.02
Squared discounted MSFE (1.00)	**0.89**	**0.86**	0.90	0.93	0.94	0.97	0.99	1.02
Forecast combinations, pre-selected predictors								
Median	**0.89**	**0.86**	**0.88**	0.92	0.95	0.97	0.97	0.99
Mean	**0.89**	**0.85**	**0.87**	0.90	0.92	0.96	0.97	1.00
Trimmed mean (5% trimming)	**0.89**	**0.85**	**0.88**	0.91	0.94	0.96	0.97	0.99
Discounted MSFE (0.90)	**0.88**	**0.84**	**0.86**	0.89	0.91	0.95	0.97	1.00
Discounted MSFE (0.95)	**0.88**	**0.84**	**0.86**	0.89	0.92	0.95	0.97	1.00
Discounted MSFE (1.00)	**0.88**	**0.84**	**0.86**	0.90	0.92	0.95	0.97	1.00
Squared discounted MSFE (0.90)	**0.87**	**0.83**	**0.84**	0.88	0.90	0.94	0.98	1.02
Squared discounted MSFE (0.95)	**0.87**	**0.83**	**0.85**	0.88	0.90	0.95	0.98	1.02
Squared discounted MSFE (1.00)	**0.87**	**0.84**	**0.85**	0.89	0.91	0.95	0.99	1.02
3. Construction, GVA								
Random walk benchmark, RMSFE	6.19	9.78	13.95	18.69	19.51	20.32	21.32	22.41
AR(AIC)	**0.77**	**0.80**	**0.79**	0.86	0.86	0.91	0.92	0.97
AR(BIC)	**0.78**	**0.81**	0.84	0.92	0.93	0.97	0.98	0.99
AR(1)	**0.91**	**0.91**	**0.88**	0.99	0.94	0.96	0.97	0.98
AR(4)	**0.79**	**0.79**	**0.79**	0.84	0.85	0.91	0.93	0.98
Forecast combinations, all predictors								
Median	**0.80**	**0.81**	0.82	0.91	0.90	0.93	0.94	0.97
Mean	**0.80**	**0.81**	0.82	0.92	0.91	0.93	0.94	0.97
Trimmed mean (5% trimming)	**0.80**	**0.81**	0.83	0.93	0.92	0.94	0.95	0.97
Discounted MSFE (0.90)	**0.80**	**0.81**	0.82	0.92	0.91	0.93	0.94	0.97
Discounted MSFE (0.95)	**0.80**	**0.81**	0.83	0.93	0.91	0.93	0.94	0.97
Discounted MSFE (1.00)	**0.80**	**0.81**	0.83	0.93	0.91	0.93	0.94	0.97
Squared discounted MSFE (0.90)	**0.79**	**0.81**	0.82	0.92	0.91	0.93	0.95	0.98
Squared discounted MSFE (0.95)	**0.79**	**0.81**	0.83	0.93	0.91	0.93	0.95	0.97
Squared discounted MSFE (1.00)	**0.79**	**0.81**	0.83	0.93	0.91	0.93	0.95	0.97
Forecast combinations, pre-selected predictors								
Median	**0.79**	**0.81**	0.81	0.90	0.89	0.92	0.93	0.96
Mean	**0.80**	**0.81**	**0.81**	0.90	0.88	0.90	0.92	0.95
Trimmed mean (5% trimming)	**0.80**	**0.81**	**0.82**	0.91	0.90	0.92	0.93	0.96
Discounted MSFE (0.90)	**0.80**	**0.81**	0.81	0.90	0.88	0.90	0.92	0.96
Discounted MSFE (0.95)	**0.80**	**0.81**	0.81	0.90	0.88	0.90	0.92	0.95
Discounted MSFE (1.00)	**0.80**	**0.81**	0.81	0.90	0.88	0.90	0.92	0.95
Squared discounted MSFE (0.90)	**0.80**	**0.81**	0.81	0.90	0.87	0.89	0.91	0.96
Squared discounted MSFE (0.95)	**0.80**	**0.81**	0.82	0.90	0.88	0.89	0.91	0.95
Squared discounted MSFE (1.00)	**0.80**	**0.81**	0.82	0.90	0.88	0.90	0.91	0.95

TABLE 3 (continued)

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
4. Trade, transport, accommodation & food, GVA								
Random walk benchmark, RMSFE	1.44	2.49	3.59	4.86	5.19	5.45	5.70	6.00
AR(AIC)	**0.89**	**0.88**	**0.90**	0.96	0.98	0.99	1.00	1.00
AR(BIC)	**0.92**	0.93	0.95	0.99	1.00	1.00	1.00	1.00
AR(1)	**0.94**	0.95	0.92	0.95	0.96	0.96	0.99	0.99
AR(4)	**0.87**	**0.88**	**0.88**	**0.91**	0.95	0.98	1.00	1.01
Forecast combinations, all predictors								
Median	**0.79**	**0.77**	**0.80**	**0.86**	0.93	0.98	1.00	1.01
Mean	**0.78**	**0.73**	**0.77**	**0.84**	0.90	0.97	1.00	1.02
Trimmed mean (5% trimming)	**0.78**	**0.74**	**0.79**	**0.85**	0.91	0.98	1.01	1.03
Discounted MSFE (0.90)	**0.77**	**0.73**	**0.78**	0.84	0.91	0.96	1.00	1.03
Discounted MSFE (0.95)	**0.78**	**0.74**	**0.78**	0.84	0.92	0.97	1.00	1.03
Discounted MSFE (1.00)	**0.78**	**0.74**	**0.78**	0.84	0.92	0.97	1.00	1.03
Squared discounted MSFE (0.90)	**0.86**	**0.72**	**0.79**	0.84	0.99	0.96	1.00	1.03
Squared discounted MSFE (0.95)	**0.86**	**0.73**	**0.80**	0.85	1.00	0.97	1.00	1.03
Squared discounted MSFE (1.00)	**0.86**	**0.73**	**0.80**	0.85	1.00	0.97	1.00	1.03
Forecast combinations, pre-selected predictors								
Median	**0.77**	**0.74**	**0.77**	**0.85**	0.92	0.98	1.00	1.01
Mean	**0.76**	**0.71**	**0.75**	**0.82**	0.89	0.96	1.00	1.02
Trimmed mean (5% trimming)	**0.77**	**0.73**	**0.76**	**0.84**	0.90	0.97	1.00	1.03
Discounted MSFE (0.90)	**0.77**	**0.72**	**0.75**	0.81	0.87	0.95	0.99	1.02
Discounted MSFE (0.95)	**0.77**	**0.72**	**0.75**	0.82	0.88	0.96	1.00	1.03
Discounted MSFE (1.00)	**0.77**	**0.73**	**0.76**	0.82	0.88	0.96	1.00	1.03
Squared discounted MSFE (0.90)	0.87	**0.75**	**0.75**	0.82	0.86	0.94	0.99	1.02
Squared discounted MSFE (0.95)	0.87	**0.76**	**0.76**	0.82	0.87	0.95	0.99	1.02
Squared discounted MSFE (1.00)	0.87	**0.76**	**0.77**	0.83	0.88	0.96	1.00	1.03
5. Information and communication, GVA								
Random walk benchmark, RMSFE	3.40	5.52	7.63	9.41	9.87	9.65	9.24	9.77
AR(AIC)	0.98	0.92	0.95	0.96	0.99	1.07	1.07	1.04
AR(BIC)	0.99	**0.88**	0.96	0.98	**0.98**	1.00	1.01	1.01
AR(1)	0.99	**0.91**	**0.94**	**0.95**	**0.96**	0.99	0.97	1.00
AR(4)	0.97	**0.89**	0.95	1.00	1.05	1.12	1.10	1.07
Forecast combinations, all predictors								
Median	0.97	**0.90**	0.95	0.97	0.97	1.08	1.05	1.04
Mean	0.98	**0.89**	0.95	0.98	0.99	1.08	1.07	1.07
Trimmed mean (5% trimming)	0.98	**0.89**	0.96	0.98	0.98	1.08	1.06	1.06
Discounted MSFE (0.90)	0.98	**0.90**	0.94	0.97	0.98	1.07	1.05	1.06
Discounted MSFE (0.95)	0.98	**0.90**	0.94	0.97	0.98	1.07	1.06	1.06
Discounted MSFE (1.00)	0.98	**0.90**	0.94	0.98	0.99	1.07	1.06	1.06
Squared discounted MSFE (0.90)	0.97	**0.91**	0.95	0.96	0.98	1.06	1.06	1.07
Squared discounted MSFE (0.95)	0.97	**0.91**	0.95	0.97	0.99	1.06	1.06	1.07
Squared discounted MSFE (1.00)	0.97	**0.91**	0.95	0.97	0.99	1.07	1.06	1.08
Forecast combinations, pre-selected predictors								
Median	1.00	**0.90**	0.93	0.93	**0.92**	1.02	0.98	1.03
Mean	1.00	**0.90**	0.93	0.95	0.93	1.03	1.00	1.07
Trimmed mean (5% trimming)	1.00	**0.91**	0.93	0.95	0.93	1.03	1.00	1.05
Discounted MSFE (0.90)	0.99	**0.90**	0.92	0.94	0.95	1.04	1.00	1.05
Discounted MSFE (0.95)	0.99	**0.90**	0.92	0.94	0.95	1.04	1.01	1.05
Discounted MSFE (1.00)	1.00	**0.90**	0.92	0.94	0.95	1.04	1.01	1.05
Squared discounted MSFE (0.90)	0.99	**0.91**	0.93	0.94	0.98	1.04	1.01	1.04
Squared discounted MSFE (0.95)	0.99	**0.91**	0.93	0.94	0.98	1.04	1.01	1.04
Squared discounted MSFE (1.00)	1.00	**0.91**	0.93	0.94	0.98	1.04	1.01	1.04
6. Financial and insurance activities, GVA								
Random walk benchmark, RMSFE	2.53	4.47	6.36	8.32	8.65	9.01	9.37	9.80
AR(AIC)	**0.47**	**0.63**	0.70	0.76	0.84	0.82	**0.82**	**0.82**
AR(BIC)	**0.47**	**0.66**	0.75	0.75	0.84	0.81	**0.79**	**0.79**
AR(1)	**0.52**	**0.68**	0.75	0.75	0.84	0.81	**0.79**	**0.79**
AR(4)	**0.46**	**0.60**	0.70	0.73	0.83	0.84	**0.83**	**0.83**
Forecast combinations, all predictors								
Median	**0.47**	**0.63**	0.74	0.75	0.83	0.80	**0.77**	**0.79**
Mean	**0.47**	**0.63**	0.74	0.76	0.82	0.78	**0.75**	**0.76**
Trimmed mean (5% trimming)	**0.47**	**0.63**	0.74	0.76	0.82	0.78	**0.76**	**0.77**
Discounted MSFE (0.90)	**0.46**	**0.62**	0.74	0.75	0.81	0.77	**0.74**	**0.76**
Discounted MSFE (0.95)	**0.46**	**0.62**	0.74	0.75	0.81	0.78	**0.74**	**0.76**
Discounted MSFE (1.00)	**0.46**	**0.62**	0.74	0.75	0.81	0.78	**0.75**	**0.76**
Squared discounted MSFE (0.90)	**0.46**	**0.64**	0.76	0.75	0.81	0.80	**0.73**	**0.75**
Squared discounted MSFE (0.95)	**0.46**	**0.64**	0.75	0.75	0.81	0.80	**0.74**	**0.76**
Squared discounted MSFE (1.00)	**0.46**	**0.64**	0.75	0.75	0.81	0.80	**0.75**	**0.77**
Forecast combinations, pre-selected predictors								
Median	**0.46**	**0.62**	0.73	0.74	0.81	0.78	**0.76**	**0.77**
Mean	**0.46**	**0.61**	0.72	0.74	0.80	0.76	**0.73**	**0.75**
Trimmed mean (5% trimming)	**0.46**	**0.61**	0.72	0.74	0.80	0.76	**0.74**	**0.76**
Discounted MSFE (0.90)	**0.45**	**0.60**	0.72	0.73	0.79	0.75	**0.72**	**0.74**
Discounted MSFE (0.95)	**0.45**	**0.60**	0.72	0.73	0.79	**0.75**	**0.73**	**0.74**
Discounted MSFE (1.00)	**0.45**	**0.60**	0.72	0.73	0.79	**0.75**	**0.73**	**0.75**
Squared discounted MSFE (0.90)	**0.44**	**0.59**	0.74	0.74	0.79	0.74	**0.72**	**0.75**
Squared discounted MSFE (0.95)	**0.44**	**0.59**	0.74	0.74	0.79	**0.75**	**0.73**	**0.76**
Squared discounted MSFE (1.00)	**0.44**	**0.60**	0.73	0.74	0.79	**0.75**	**0.74**	**0.77**

TABLE 3 (continued)

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
7. Real estate activities, GVA								
Random walk benchmark, RMSFE	0.51	1.04	1.57	2.13	2.23	2.33	2.42	2.54
AR(AIC)	**0.49**	**0.57**	0.65	**0.63**	0.72	0.74	0.79	0.80
AR(BIC)	**0.47**	**0.55**	0.65	0.63	0.72	0.76	0.86	0.87
AR(1)	**0.43**	**0.49**	**0.57**	**0.65**	**0.74**	0.80	0.83	0.85
AR(4)	**0.48**	**0.56**	**0.64**	**0.62**	0.72	0.73	0.79	0.80
Forecast combinations, all predictors								
Median	**0.48**	**0.56**	0.64	**0.62**	0.71	0.72	0.78	0.80
Mean	**0.48**	**0.56**	0.63	**0.61**	0.69	0.71	0.78	0.81
Trimmed mean (5% trimming)	**0.48**	**0.56**	0.63	**0.62**	0.70	0.72	0.78	0.81
Discounted MSFE (0.90)	**0.48**	**0.56**	0.63	**0.61**	0.68	0.71	0.77	0.81
Discounted MSFE (0.95)	**0.48**	**0.56**	0.63	**0.61**	0.68	0.71	0.77	0.81
Discounted MSFE (1.00)	**0.48**	**0.56**	0.63	**0.61**	0.69	0.71	0.78	0.81
Squared discounted MSFE (0.90)	**0.48**	**0.56**	0.62	**0.61**	0.68	0.71	0.77	0.81
Squared discounted MSFE (0.95)	**0.48**	**0.56**	0.62	**0.61**	0.68	0.71	0.77	0.81
Squared discounted MSFE (1.00)	**0.48**	**0.55**	0.62	**0.61**	0.69	0.71	0.78	0.81
Forecast combinations, pre-selected predictors								
Median	**0.47**	**0.56**	**0.63**	**0.61**	0.70	0.72	0.78	0.80
Mean	**0.47**	**0.56**	**0.62**	**0.60**	0.67	0.69	0.76	0.80
Trimmed mean (5% trimming)	**0.47**	**0.56**	**0.62**	**0.61**	0.68	0.70	0.77	0.80
Discounted MSFE (0.90)	**0.47**	**0.55**	**0.61**	**0.58**	0.66	0.68	0.76	0.80
Discounted MSFE (0.95)	**0.47**	**0.55**	**0.61**	**0.59**	0.66	0.68	0.76	0.80
Discounted MSFE (1.00)	**0.47**	**0.55**	**0.61**	**0.59**	0.66	0.68	0.76	0.80
Squared discounted MSFE (0.90)	**0.47**	**0.55**	**0.60**	**0.57**	0.64	0.68	0.76	0.81
Squared discounted MSFE (0.95)	**0.47**	**0.55**	**0.61**	**0.58**	0.65	0.68	0.76	0.81
Squared discounted MSFE (1.00)	**0.47**	**0.55**	**0.61**	**0.58**	0.65	0.68	0.76	0.81
8. Professional and administrative activities, GVA								
Random walk benchmark, RMSFE	1.80	3.05	4.22	5.13	5.23	5.38	5.49	5.50
AR(AIC)	0.98	0.98	0.98	0.99	1.03	1.03	1.03	1.00
AR(BIC)	1.00	1.02	1.02	1.01	1.00	1.02	**0.99**	1.00
AR(1)	0.96	0.95	0.95	0.97	1.01	1.04	1.04	1.03
AR(4)	0.98	0.96	0.99	1.01	1.03	1.05	1.05	1.03
Forecast combinations, all predictors								
Median	**0.92**	0.95	0.94	0.97	0.99	1.02	1.02	1.02
Mean	**0.92**	0.93	0.95	0.97	1.02	1.05	1.06	1.07
Trimmed mean (5% trimming)	**0.92**	0.93	0.94	0.97	1.00	1.03	1.05	1.06
Discounted MSFE (0.90)	**0.91**	0.93	0.96	0.96	1.00	1.05	1.08	1.10
Discounted MSFE (0.95)	**0.91**	0.93	0.96	0.97	1.01	1.05	1.08	1.10
Discounted MSFE (1.00)	**0.91**	0.93	0.95	0.97	1.01	1.06	1.08	1.10
Squared discounted MSFE (0.90)	**0.91**	0.93	0.99	0.97	1.10	1.06	1.11	1.15
Squared discounted MSFE (0.95)	**0.91**	0.92	0.98	0.97	1.10	1.07	1.11	1.15
Squared discounted MSFE (1.00)	**0.91**	0.92	0.97	0.98	1.11	1.07	1.11	1.15
Forecast combinations, pre-selected predictors								
Median	**0.91**	0.93	0.93	0.95	0.98	1.01	1.02	1.03
Mean	**0.90**	0.92	0.94	0.96	1.00	1.04	1.05	1.08
Trimmed mean (5% trimming)	**0.90**	0.92	0.93	0.95	0.99	1.02	1.04	1.06
Discounted MSFE (0.90)	**0.90**	0.91	0.95	0.95	0.99	1.04	1.07	1.11
Discounted MSFE (0.95)	**0.90**	0.91	0.95	0.95	0.99	1.04	1.07	1.11
Discounted MSFE (1.00)	**0.90**	0.92	0.95	0.96	1.00	1.05	1.07	1.11
Squared discounted MSFE (0.90)	**0.89**	0.92	0.98	0.95	0.98	1.06	1.10	1.14
Squared discounted MSFE (0.95)	**0.89**	0.92	0.97	0.95	0.99	1.06	1.11	1.14
Squared discounted MSFE (1.00)	**0.90**	0.92	0.96	0.96	1.00	1.06	1.11	1.15
9. Public administration education and health, GVA								
Random walk benchmark, RMSFE	1.60	1.73	2.08	2.75	2.89	2.96	3.10	3.23
AR(AIC)	1.16	1.30	1.27	1.47	1.04	1.08	1.02	1.07
AR(BIC)	1.16	1.30	1.23	1.47	1.04	1.05	1.02	1.01
AR(1)	1.07	0.97	1.04	1.04	1.04	1.05	1.01	1.02
AR(4)	1.13	1.40	1.24	1.49	1.09	1.08	1.04	1.09
Forecast combinations, all predictors								
Median	1.22	1.19	1.20	1.41	1.02	1.06	1.02	1.05
Mean	1.23	1.19	1.19	1.34	1.02	1.05	1.01	1.04
Trimmed mean (5% trimming)	1.24	1.18	1.19	1.35	1.02	1.05	1.01	1.04
Discounted MSFE (0.90)	1.24	1.15	1.19	1.15	1.01	1.04	1.00	1.03
Discounted MSFE (0.95)	1.24	1.16	1.19	1.16	1.01	1.04	1.00	1.03
Discounted MSFE (1.00)	1.24	1.16	1.19	1.16	1.01	1.04	1.00	1.03
Squared discounted MSFE (0.90)	1.24	1.26	1.19	1.04	1.00	1.04	1.00	1.02
Squared discounted MSFE (0.95)	1.24	1.27	1.19	1.05	1.00	1.04	1.00	1.02
Squared discounted MSFE (1.00)	1.24	1.27	1.19	1.06	1.00	1.03	1.00	1.02
Forecast combinations, pre-selected predictors								
Median	1.24	1.16	1.19	1.38	1.02	1.06	1.02	1.04
Mean	1.26	1.18	1.19	1.31	1.02	1.05	1.01	1.03
Trimmed mean (5% trimming)	1.26	1.18	1.18	1.32	1.01	1.05	1.01	1.04
Discounted MSFE (0.90)	1.26	1.16	1.19	1.12	1.01	1.04	0.99	1.02
Discounted MSFE (0.95)	1.26	1.16	1.19	1.12	1.01	1.04	0.99	1.02
Discounted MSFE (1.00)	1.26	1.16	1.19	1.13	1.00	1.03	0.99	1.02
Squared discounted MSFE (0.90)	1.27	1.26	1.19	1.01	1.00	1.03	0.98	1.01
Squared discounted MSFE (0.95)	1.27	1.26	1.20	1.03	1.00	1.03	0.98	1.01
Squared discounted MSFE (1.00)	1.27	1.27	1.20	1.04	1.00	1.03	0.97	1.01

TABLE 3 (continued)

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
10. Other services, GVA								
Random walk benchmark, RMSFE	1.74	3.07	4.54	6.09	6.27	6.49	6.70	6.98
AR(AIC)	0.92	0.96	0.97	1.09	1.14	1.17	1.16	1.14
AR(BIC)	0.97	0.93	0.95	1.09	1.13	1.17	1.15	1.13
AR(1)	0.92	0.86	0.87	0.94	0.99	1.02	1.03	1.04
AR(4)	0.93	0.93	0.97	1.09	1.14	1.17	1.16	1.14
Forecast combinations, all predictors								
Median	0.91	0.90	0.91	1.05	1.11	1.15	1.12	1.12
Mean	**0.89**	0.89	0.91	1.03	1.09	1.13	1.11	1.11
Trimmed mean (5% trimming)	**0.90**	0.89	0.91	1.04	1.10	1.14	1.11	1.11
Discounted MSFE (0.90)	**0.89**	0.90	0.91	1.03	1.09	1.13	1.11	1.11
Discounted MSFE (0.95)	**0.89**	0.90	0.91	1.03	1.09	1.13	1.11	1.11
Discounted MSFE (1.00)	**0.89**	0.90	0.91	1.03	1.09	1.14	1.11	1.11
Squared discounted MSFE (0.90)	**0.89**	0.89	0.91	1.06	1.09	1.13	1.11	1.11
Squared discounted MSFE (0.95)	**0.89**	0.89	0.91	1.06	1.09	1.13	1.11	1.11
Squared discounted MSFE (1.00)	**0.90**	0.90	0.91	1.06	1.10	1.14	1.11	1.11
Forecast combinations, pre-selected predictors								
Median	0.90	0.89	0.89	1.02	1.09	1.13	1.11	1.10
Mean	**0.89**	0.89	0.89	1.01	1.07	1.11	1.09	1.10
Trimmed mean (5% trimming)	**0.89**	0.89	0.89	1.01	1.07	1.11	1.09	1.09
Discounted MSFE (0.90)	**0.89**	0.88	0.89	1.00	1.06	1.11	1.09	1.10
Discounted MSFE (0.95)	**0.89**	0.88	0.90	1.01	1.07	1.11	1.09	1.10
Discounted MSFE (1.00)	**0.89**	0.89	0.90	1.01	1.07	1.12	1.09	1.10
Squared discounted MSFE (0.90)	**0.88**	0.87	0.90	1.01	1.06	1.10	1.08	1.09
Squared discounted MSFE (0.95)	**0.88**	0.87	0.90	1.01	1.06	1.11	1.09	1.10
Squared discounted MSFE (1.00)	**0.89**	0.88	0.91	1.02	1.07	1.12	1.10	1.10
11. Import duties and VAT								
Random walk benchmark, RMSFE	2.34	3.42	3.99	4.33	4.37	4.62	4.85	5.10
AR(AIC)	0.92	0.92	0.98	0.99	1.02	1.01	1.04	1.00
AR(BIC)	0.96	1.01	0.97	1.01	1.00	1.00	1.04	1.00
AR(1)	1.05	1.00	0.97	0.99	1.02	1.02	1.06	1.00
AR(4)	0.92	0.90	0.91	0.95	1.00	1.04	1.03	0.98
Forecast combinations, all predictors								
Median	0.91	**0.88**	**0.89**	**0.93**	0.97	1.00	1.01	0.99
Mean	0.90	**0.87**	**0.86**	**0.91**	0.94	0.98	1.00	0.99
Trimmed mean (5% trimming)	0.90	**0.87**	**0.87**	**0.92**	0.95	1.00	1.01	0.99
Discounted MSFE (0.90)	0.91	**0.86**	**0.85**	**0.90**	0.94	0.98	1.00	0.99
Discounted MSFE (0.95)	0.91	**0.86**	**0.85**	**0.90**	0.94	0.98	1.00	0.99
Discounted MSFE (1.00)	0.91	**0.86**	**0.85**	**0.90**	0.94	0.98	1.00	0.99
Squared discounted MSFE (0.90)	0.92	**0.84**	**0.83**	**0.89**	0.93	0.98	1.00	1.00
Squared discounted MSFE (0.95)	0.92	**0.85**	**0.83**	**0.89**	0.93	0.98	1.00	1.00
Squared discounted MSFE (1.00)	0.92	**0.85**	**0.83**	**0.89**	0.93	0.98	1.00	1.00
Forecast combinations, pre-selected predictors								
Median	0.90	**0.86**	**0.86**	**0.89**	0.94	0.98	1.00	0.98
Mean	0.90	**0.84**	**0.83**	**0.86**	**0.90**	0.95	0.97	0.97
Trimmed mean (5% trimming)	0.90	**0.85**	**0.84**	**0.88**	0.92	0.97	0.99	0.98
Discounted MSFE (0.90)	0.90	**0.84**	**0.82**	**0.85**	0.90	0.94	0.97	0.97
Discounted MSFE (0.95)	0.90	**0.84**	**0.82**	**0.86**	0.90	0.94	0.97	0.97
Discounted MSFE (1.00)	0.90	**0.84**	**0.82**	**0.86**	0.90	0.94	0.97	0.97
Squared discounted MSFE (0.90)	0.91	**0.83**	**0.81**	**0.85**	0.89	0.93	0.96	0.97
Squared discounted MSFE (0.95)	0.91	**0.83**	**0.81**	**0.86**	0.89	0.93	0.96	0.97
Squared discounted MSFE (1.00)	0.91	**0.84**	**0.81**	**0.86**	0.90	0.93	0.96	0.97

Notes: Entries in bold denote statistical significance at 10% level of the modified Diebold-Mariano test of equal forecast accuracy (Diebold and Mariano 1995; Harvey et al. 1997). The tests compare the forecast errors from the benchmark model (random walk) to those from the forecast combinations or univariate models shown in the table.

AR(AIC) and AR(BIC) denote the autoregressive models with lag length selected using the Akaike and Bayesian information criteria, respectively; AR(1) and AR(4) are the autoregressive models of order one and four, respectively.

For the discounted and squared discounted MSFE forecast combination methods the discount factor is given in parentheses.

Information from macroeconomic and financial predictors improves on the accuracy of naïve forecasts in the case of financial and insurance activities, real estate activities, and import duties. Moreover, forecasts for the abovementioned components based on a set of pre-selected predictors are associated with somewhat lower error than forecasts computed using the full dataset. In the financial and insurance sector, the improvements over the random walk model are significant for short (one and two) and longer (six to eight) horizons. In the sector of real estate activities, the MSFE reduction vis-à-vis the benchmark is found to be statistically significant for one- to four-quarter ahead forecasts. Combination forecasts for the growth rate of import duties generate gains that are significant for horizons of two to four quarters.

4.2 GDP growth: direct approach vs bottom-up approach

The models and forecast combinations discussed in section 2 are also applied to modelling and forecasting GDP growth. The direct approach to GDP forecasting amounts to directly computing the forecasts from GDP growth models (univariate, ADL, factor-augmented). Alternatively, a bottom-up approach to forecasting GDP can be employed whereby GDP growth forecasts can be computed by aggregating the component forecasts obtained from models for the production-side components. In the second instance, the resulting GDP growth forecasts are known as bottom-up forecasts, i.e. they are constructed by adding up the forecasts for all the production-side components of GDP.

We compute a bottom-up GDP growth forecast by aggregating the component forecasts obtained via *forecast combinations*, i.e.

$$\hat{Z}_{t+h}^{(GDP,k)} = \sum_{s=1}^{S} \hat{Z}_{t+h}^{(s,k)}$$

where $\hat{Z}_{t+h}^{(s,k)}$ is the forecasted level of component s implied by the corresponding component growth forecast for period $t+h$ based on forecast combination k, constructed with information up to period t; $\hat{Z}_{t+h}^{(GDP,k)}$ is the resulting forecast for the level of GDP, which is transformed into growth rate prior to evaluating the forecasting performance.[16]

Table 4 compares the performance of GDP growth forecasts from the direct and bottom-up approaches. The benchmark for comparisons is the random walk model for GDP. The entries in bold indicate a superior performance vis-à-vis the naïve benchmark, with the difference in performance being statistically significant.

The use of information from macroeconomic and financial indicators enhances the accuracy of GDP growth forecasts. Both direct and bottom-up approaches yield gains over the random walk benchmark and, in most cases, over the autoregressive models for GDP growth; nevertheless, the forecast gains decline towards the end of the horizon.

[16] Another method of computing bottom-up GDP forecasts is by aggregating the component forecasts obtained from the *individual single equation models* (as opposed to forecast combinations) and subsequently combining the individual aggregate forecasts using combination methods, as discussed in the Appendix (section A3). For brevity, the results of this method are presented in the Appendix (Table A2) as the forecasting performance is very similar to that of the bottom-up approach discussed in this section.

TABLE 4

RMSFE relative to random walk, GDP growth

Forecast horizon (quarters)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Direct approach								
Random walk benchmark, RMSFE	1.10	2.09	3.15	4.25	4.46	4.68	4.92	5.17
AR(AIC)	**0.81**	**0.78**	**0.77**	**0.78**	0.84	0.90	0.92	0.95
AR(BIC)	**0.82**	**0.77**	**0.76**	0.82	0.91	0.98	0.99	0.99
AR(1)	**0.90**	**0.84**	**0.84**	**0.84**	0.89	0.92	0.94	0.96
AR(4)	**0.79**	**0.76**	**0.75**	**0.78**	0.86	0.92	0.94	0.97
Forecast combinations, all predictors								
Median	**0.74**	**0.70**	**0.71**	**0.76**	0.84	0.91	0.92	0.95
Mean	**0.73**	**0.68**	**0.69**	**0.74**	0.82	0.89	0.91	0.95
Trimmed mean (5% trimming)	**0.73**	**0.68**	**0.70**	**0.75**	0.84	0.90	0.92	0.96
Discounted MSFE (0.90)	**0.72**	**0.66**	**0.70**	**0.73**	0.81	0.88	0.91	0.95
Discounted MSFE (0.95)	**0.73**	**0.67**	**0.70**	**0.73**	0.81	0.88	0.91	0.95
Discounted MSFE (1.00)	**0.73**	**0.67**	**0.70**	**0.73**	0.82	0.89	0.91	0.95
Squared discounted MSFE (0.90)	**0.72**	**0.65**	**0.70**	**0.72**	0.79	0.86	0.90	0.95
Squared discounted MSFE (0.95)	**0.73**	**0.65**	**0.70**	**0.73**	0.80	0.88	0.91	0.95
Squared discounted MSFE (1.00)	**0.74**	**0.65**	**0.71**	**0.73**	0.81	0.88	0.91	0.95
Forecast combinations, pre-selected predictors								
Median	**0.73**	**0.68**	**0.69**	**0.74**	0.83	0.90	0.92	0.95
Mean	**0.72**	**0.66**	**0.68**	**0.72**	**0.81**	0.88	0.90	0.94
Trimmed mean (5% trimming)	**0.72**	**0.67**	**0.69**	**0.74**	**0.82**	0.90	0.92	0.95
Discounted MSFE (0.90)	**0.72**	**0.65**	**0.67**	**0.71**	0.79	0.86	0.90	0.94
Discounted MSFE (0.95)	**0.72**	**0.65**	**0.67**	**0.72**	0.79	0.87	0.90	0.94
Discounted MSFE (1.00)	**0.73**	**0.65**	**0.67**	**0.72**	0.80	0.87	0.90	0.94
Squared discounted MSFE (0.90)	**0.71**	**0.64**	**0.66**	**0.70**	0.76	0.83	0.89	0.94
Squared discounted MSFE (0.95)	**0.72**	**0.64**	**0.66**	**0.71**	0.78	0.85	0.89	0.95
Squared discounted MSFE (1.00)	**0.72**	**0.64**	**0.66**	**0.71**	0.79	0.86	0.90	0.95
Bottom-up approach								
Based on the following component forecast combinations, (all predictors):								
Median	**0.78**	**0.75**	**0.80**	0.88	0.91	0.96	0.98	1.01
Mean	**0.78**	**0.73**	**0.78**	**0.87**	0.89	0.95	0.97	1.01
Trimmed mean (5% trimming)	**0.78**	**0.74**	**0.79**	**0.87**	0.90	0.96	0.98	1.01
Discounted MSFE (0.90)	**0.78**	**0.72**	**0.77**	**0.85**	0.88	0.94	0.97	1.01
Discounted MSFE (0.95)	**0.78**	**0.73**	**0.78**	**0.86**	0.88	0.94	0.97	1.01
Discounted MSFE (1.00)	**0.78**	**0.73**	**0.78**	**0.86**	0.88	0.94	0.98	1.01
Squared discounted MSFE (0.90)	**0.80**	**0.72**	**0.77**	**0.84**	0.87	0.93	0.97	1.01
Squared discounted MSFE (0.95)	**0.81**	**0.73**	**0.77**	**0.85**	0.88	0.94	0.97	1.02
Squared discounted MSFE (1.00)	**0.81**	**0.74**	**0.78**	**0.85**	0.89	0.94	0.98	1.02
Based on the following component forecast combinations (pre-selected predictors):								
Median	**0.76**	**0.73**	**0.77**	**0.84**	**0.88**	0.94	0.96	1.00
Mean	**0.75**	**0.71**	**0.75**	**0.82**	**0.86**	0.92	0.95	0.99
Trimmed mean (5% trimming)	**0.76**	**0.72**	**0.76**	**0.84**	**0.87**	0.93	0.96	1.00
Discounted MSFE (0.90)	**0.76**	**0.70**	**0.74**	**0.81**	**0.84**	0.91	0.94	0.99
Discounted MSFE (0.95)	**0.76**	**0.71**	**0.74**	**0.81**	**0.85**	0.91	0.95	1.00
Discounted MSFE (1.00)	**0.76**	**0.71**	**0.75**	**0.82**	**0.85**	0.91	0.95	1.00
Squared discounted MSFE (0.90)	**0.77**	**0.70**	**0.73**	**0.79**	0.82	0.89	0.94	0.99
Squared discounted MSFE (0.95)	**0.78**	**0.71**	**0.74**	**0.80**	0.83	0.90	0.94	1.00
Squared discounted MSFE (1.00)	**0.79**	**0.72**	**0.74**	**0.81**	**0.84**	0.91	0.95	1.00

Notes: Entries in bold denote statistical significance at 10% level of the modified Diebold-Mariano test of equal forecast accuracy (Diebold and Mariano 1995; Harvey et al. 1997). The tests compare the forecast errors from the benchmark model (random walk) to those from the forecast combinations or univariate models shown in the table.

AR(AIC) and AR(BIC) denote the autoregressive models with lag length selected using the Akaike and Bayesian information criteria, respectively; AR(1) and AR(4) are the autoregressive models of order one and four, respectively.

For the discounted and squared discounted MSFE forecast combination methods the discount factor is given in parentheses.

GDP growth forecasts from the direct approach, constructed using forecast combinations are significantly more precise than the naïve forecasts for horizons of one to five quarters. Discounted MSFE combination methods from the direct approach seem to generate somewhat lower relative errors. In the direct approach, combination forecasts computed from a set of pre-selected predictors highly correlated with GDP growth, lead to marginal improvements in the forecasting performance vis-à-vis combinations of aggregate forecasts incorporating information from the full set of indicators.

Bottom-up GDP growth forecasts lead to significantly lower RMSE than the naïve forecasts from the direct approach for horizons of up to five quarters ahead. Bottom-up forecasts based on pre-selected predictors for each sector are associated with lower forecast error than bottom-up forecasts that make use of all predictors in the dataset.

To determine whether the difference in the forecasting performance of direct and bottom-up approaches is statistically significant we carry out hypothesis tests. We test whether the forecasting performance (measured by the mean squared error) of the squared discounted MSFE (with discount factor equal to 0.90) combinations of GDP growth forecasts computed directly using all available predictors, is the same as that of the other forecasting methods from the two approaches presented in Table 4. This hypothesis is tested against the alternative of lower mean squared error in the case of the abovementioned squared discounted MSFE forecast combination. The reason for choosing this particular forecast combination as the benchmark is because it is the combination with the smallest relative RMSE for all horizons that incorporates information from all predictors in the dataset (Table 4); it is also the method that has been applied to compute the GDP growth projections published by the Economics Research Centre. The comparison of the forecasting performance is shown in Table 5; the entries in bold indicate that the difference in terms of predictive accuracy between the benchmark and the method tested is statistically significant, with the mean square error of the benchmark being smaller.[17]

Looking at the combination methods in the case of the direct approach, we find that the difference in predictive performance between the benchmark and forecast combinations based on all the predictors is statistically significant for simple combinations and discounted MSFE combinations (with discount factor 0.90 and 0.95) when forecasts are computed two quarters ahead. The forecast accuracy of combinations based on a sub-set of predictors that are significantly correlated with GDP growth, does not differ from that of the benchmark.

The forecasting performance of the bottom-up approach is in general inferior to that of the benchmark and therefore forecasts from the direct approach. Bottom-up forecasts computed using information from all predictors in the dataset are significantly worse than the directly generated benchmark forecasts for the largest part of the horizon. Nevertheless, bottom-up forecasts constructed using pre-selected predictors for each sector and squared discounted combinations for the component forecasts, are not found to significantly differ from the benchmark forecasts in terms of precision.

[17] The results from the alternative method of computing bottom-up GDP growth forecasts described in footnote 16 and in the Appendix (section A3) are shown in Table A3 (Appendix).

TABLE 5

RMSFE relative to squared discounted MSFE (0.90) combination from the direct approach, GDP growth

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
Direct approach								
Forecast combinations, all predictors								
Benchmark: Squared discounted MSFE (0.90), RMSFE	0.80	1.36	2.21	3.08	3.52	4.05	4.44	4.92
Median	1.02	**1.07**	1.01	1.05	1.06	1.05	1.02	1.00
Mean	1.00	**1.04**	0.99	1.03	1.04	1.03	1.01	1.00
Trimmed mean (5% trimming)	1.01	**1.05**	1.00	1.04	1.06	1.05	1.02	1.01
Discounted MSFE (0.90)	1.00	**1.02**	0.99	1.01	1.03	1.02	1.01	1.00
Discounted MSFE (0.95)	1.00	**1.02**	0.99	1.01	1.03	1.02	1.01	1.00
Discounted MSFE (1.00)	1.01	1.03	0.99	1.02	1.03	1.03	1.01	1.00
Squared discounted MSFE (0.95)	1.01	1.00	1.00	1.01	1.01	1.01	1.01	1.00
Squared discounted MSFE (1.00)	1.02	1.01	1.00	1.01	1.02	1.02	1.01	1.00
Forecast combinations, pre-selected predictors								
Median	1.01	1.04	0.98	1.03	1.05	1.04	1.02	1.00
Mean	0.99	1.02	0.96	1.00	1.02	1.01	1.00	0.99
Trimmed mean (5% trimming)	0.99	1.03	0.98	1.02	1.04	1.04	1.02	1.00
Discounted MSFE (0.90)	1.00	1.00	0.95	0.98	1.00	1.00	0.99	0.99
Discounted MSFE (0.95)	1.00	1.00	0.95	0.99	1.01	1.00	1.00	0.99
Discounted MSFE (1.00)	1.00	1.01	0.95	0.99	1.01	1.01	1.00	0.99
Squared discounted MSFE (0.90)	0.98	0.98	0.94	0.97	0.96	0.96	0.98	0.99
Squared discounted MSFE (0.95)	0.99	0.99	0.94	0.98	0.98	0.98	0.99	0.99
Squared discounted MSFE (1.00)	1.00	0.99	0.94	0.98	0.99	0.99	1.00	0.99
Bottom-up approach								
Based on the following component forecast combinations, (all predictors):								
Median	1.08	**1.16**	1.13	**1.21**	1.15	1.11	1.09	**1.06**
Mean	1.07	**1.13**	1.11	**1.20**	1.13	1.10	**1.08**	**1.06**
Trimmed mean (5% trimming)	1.08	**1.14**	1.12	**1.21**	1.14	1.11	**1.09**	**1.06**
Discounted MSFE (0.90)	1.07	**1.11**	1.10	**1.18**	1.12	1.09	**1.08**	**1.06**
Discounted MSFE (0.95)	1.08	**1.12**	1.10	**1.18**	1.12	1.09	**1.08**	**1.06**
Discounted MSFE (1.00)	1.08	**1.13**	1.10	**1.19**	1.12	1.09	**1.08**	**1.06**
Squared discounted MSFE (0.90)	1.11	**1.11**	1.09	**1.16**	**1.11**	**1.08**	**1.07**	**1.06**
Squared discounted MSFE (0.95)	1.11	**1.13**	1.10	**1.17**	**1.12**	**1.09**	**1.08**	**1.07**
Squared discounted MSFE (1.00)	1.12	**1.14**	1.10	**1.18**	**1.12**	1.09	**1.09**	**1.07**
Based on the following component forecast combinations (pre-selected predictors):								
Median	1.05	1.12	1.09	1.16	1.12	1.09	1.07	**1.05**
Mean	1.04	1.10	1.06	1.14	1.08	1.06	**1.05**	1.04
Trimmed mean (5% trimming)	1.04	1.11	1.07	**1.15**	1.10	1.08	**1.06**	**1.05**
Discounted MSFE (0.90)	1.04	1.08	1.05	1.12	1.07	1.05	**1.05**	1.04
Discounted MSFE (0.95)	1.05	1.09	1.06	1.12	1.07	1.05	**1.05**	1.05
Discounted MSFE (1.00)	1.05	1.09	1.06	1.13	1.07	1.05	**1.05**	1.05
Squared discounted MSFE (0.90)	1.07	1.08	1.04	1.10	1.04	1.03	1.04	1.04
Squared discounted MSFE (0.95)	1.08	1.09	1.05	1.11	1.05	1.04	1.05	1.05
Squared discounted MSFE (1.00)	1.09	1.10	1.06	1.12	1.06	1.05	**1.05**	1.05

Notes: Entries in bold denote statistical significance at 10% level of the modified Diebold-Mariano test of equal forecast accuracy (Diebold and Mariano 1995; Harvey et al. 1997). The tests compare the forecast errors from the benchmark model (squared discounted MSFE with a discount factor equal to 0.90) to those from the methods listed in the table.

For the discounted and squared discounted MSFE forecast combination methods the discount factor is given in parentheses.

5. Constrained sectoral forecasts

5.1 Models and forecast combinations

In the previous section, we find evidence that forecasting GDP growth directly is, in general, superior in terms of accuracy compared to computing bottom-up forecasts by aggregating component forecasts. In order to directly compute GDP growth forecasts, which are associated with lower forecast errors, and, at the same time, obtain forecasts for the growth rates of the production-side components that satisfy the adding up restriction in the national accounts, we resort to estimating constrained models for the components. More specifically, the forecasting models for the growth contribution of each production-side component have the same specification (i.e. the same set of predictors) as the forecasting models for GDP growth. This is equivalent to estimating a Seemingly Unrelated Regressions (SUR) model for the growth contributions of the production-side components with identical regressors; the sum of the forecasts for the growth contributions of components equals the GDP growth forecasts obtained directly.

As an example, we consider the case of the FADL model given in (3b); let $y_{t+h}^{h,GDP}$ denote the growth rate of GDP

$$y_{t+h}^{h,GDP} = \zeta + \sum_{i=0}^{q*} \kappa_i y_{t-i}^{GDP} + \sum_{i=0}^{p*} \lambda_i x_{t-i} + \mu' x_{t+1}^{L}$$
$$+ \sum_{i=0}^{l*} \rho_i \hat{f}_{t-i} + \pi' r_{t+1}^{L} + \varepsilon_{t+h}^{h,GDP} \quad (8)$$

where q^*, p^*, l^* denote the optimal lag length chosen for GDP growth, predictor x_t and factor $\hat{f}_t$, respectively, in each iteration. From the national accounts identity, the growth rate of GDP can be equivalently written as the weighted average of the growth rates of components, with weights equal to the contribution of each component to GDP,

$$y_t^{GDP} = \sum_{s=1}^{S} v_{t-k}^{s}\, y_t^{s} = \sum_{s=1}^{S} c_{t-k}^{s} \quad (9)$$

where $y_t^{i} = \frac{Z_t^i - Z_{t-k}^i}{Z_{t-k}^i} \approx \ln\left(\frac{Z_t^i}{Z_{t-k}^i}\right)$, i refers to GDP or component, s, $s = 1, 2, \dots, S$, Z_t^i is the level of GDP or the level of a component, $v_{t-k}^{s} = \frac{Z_{t-k}^{s}}{Z_{t-k}^{GDP}}$, and $c_{t-k}^{s} = v_{t-k}^{s} y_t^{s}$ with $k > 0$, i.e. the contribution of component's s growth to the overall growth rate of the economy.

The constrained model for component s is specified using the growth contribution, c_t^s, as follows

$$c_{t+h}^{h,s} = \zeta_s + \sum_{i=0}^{q*} \kappa_{i,s} y_{t-i}^{GDP} + \sum_{i=0}^{p*} \lambda_{i,s} x_{t-i} + \mu_s' x_{t+1}^{L}$$
$$+ \sum_{i=0}^{l*} \rho_{i,s} \hat{f}_{t-i} + \pi_s' r_{t+1}^{L} + \varepsilon_{t+h}^{h,s}, \quad \text{for all } s \quad (10)$$

i.e. the regressors in equation (10) are identical to those in equation (8). Collecting the k unknown parameters of model (8) in a $k \times 1$ vector P, we can write the OLS estimator of P as

$$\hat{P} = \sum_{s=1}^{S} \hat{P}_s \quad (11)$$

where $\hat{P}_s$ is the estimator of the $k \times 1$ vector P_s that holds the parameters of the component model in (10).[18] The equality in (11) results from the assumption of common regressors in

[18] Stacking the T observations on the regressors in (8) and (10) in a $T \times k$ matrix D and collecting the T observations on the dependent variable in (8) and (10) in a $T \times 1$ vector Y^{GDP} and a $T \times 1$ vector C^s, respectively, the OLS estimators of P and P_s are given by $\hat{P} = (D'D)^{-1}D'Y^{GDP}$ and $\hat{P}_s = \left(D'D\right)^{-1} D'C^s$, all s.

the aggregate (equation 8) and component models (equation 10), and the national accounts identity as given in (9). It then follows that a GDP growth forecast computed from model i, using information up to period t, is equal to the sum of the forecasts for the growth contributions of the components, computed from models with the same predictors as model i. Therefore, the aggregate forecast is equal to the weighted average of the component growth forecasts with sample weights, i.e.

$$\hat{y}_{i,t+h}^{h,GDP} = \sum_{s=1}^{S} \hat{c}_{i,t+h}^{h,s} = \sum_{s=1}^{S} v_t^s \hat{y}_{i,t+h}^{h,s}. \qquad (12)$$

As discussed in the previous section, the GDP growth forecasts from the direct approach that are found to perform well are computed as forecast combinations i.e. weighted averages of numerous model forecasts. Using (12), the combination forecast for GDP growth, $\hat{F}_{t+h}^{h,GDP}$, obtained from M model forecasts can be expressed in terms of the component growth forecasts

$$\begin{aligned}\hat{F}_{t+h}^{h,GDP} &= \sum_{i=1}^{M} w_{i,t} \hat{y}_{i,t+h}^{h,GDP} \\ &= \sum_{s=1}^{S} v_t^s \sum_{i=1}^{M} w_{i,t}\, \hat{y}_{i,t+h}^{h,s} \qquad (13)\end{aligned}$$

where the combination weights $w_{i,t}$ can be constant, as in the case of the mean and median, or dependent on past performance, as defined in (6) and (7). It follows from equation (13) that the combination forecasts for the component growth rates that add up to the GDP growth forecast from the direct approach, are restricted to have the same combination weights, $w_{i,t}$, as those used in the computation of the GDP growth forecast.

5.2 Performance

The results of the previous section revealed that GDP growth forecasts from the direct approach are associated with lower forecast errors compared to the bottom-up forecasts. In Table 6 we evaluate the performance of growth forecasts for the production-side components obtained subject to the constraint of adding up to the GDP growth forecasts computed directly. We also juxtapose the accuracy of the constrained component growth forecasts with that of component forecasts computed from unconstrained models (see Table 3). The constrained component forecasts are computed using the same predictors as those employed for the GDP growth forecasts presented in Table 4. More specifically, the component forecasts are computed from the following models for the components: (a) models that include lagged terms of GDP growth only, and (b) combinations of forecasts from ADL-type, FAR-type and FADL-type models in which the component's autoregressive terms are replaced with lagged terms of GDP growth. Furthermore, we compute combination forecasts based on all predictors in the dataset as well as combinations based on a set of pre-selected predictors that are significantly correlated with GDP growth. The table presents the square root MSFE (RMSFE) of the different methods relative to the random walk benchmark for the sectoral GVA and for import duties plus VAT. The entries in bold indicate that the performance of the model/method is superior vis-à-vis the naïve benchmark and the difference in performance is statistically significant.

The results show that we can achieve forecasting gains over the random walk using constrained models for most of the components. For agriculture, public administration, education and health, the constrained models do not significantly outperform the benchmark; nevertheless the same occurs if the unconstrained models are employed for forecasting GVA growth in these sectors. For professional services, the gains attained by the constrained models over the benchmark are limited; similarly, only small gains are achieved when the unconstrained models are employed. Combination forecasts from constrained models for the industrial sector significantly outperform the random walk forecast for very short horizons. The performance of forecast combinations from the constrained models is slightly inferior to that of combinations from the unconstrained models, especially when the latter are based on a set of pre-selected predictors significantly correlated with industrial output growth. For the construction sector, constrained combination forecasts are associated with significantly lower errors compared to the benchmark, for horizons of one to three quarters ahead; also, these forecasts outperform unconstrained combination forecasts for a horizon of two and three quarters.

For the largest sector of the economy, namely trade transport, accommodation and food services, the constrained models significantly improve on the benchmark up to five quarters ahead; moreover, they are associated with lower forecast errors compared to the unconstrained models. The constrained forecasts lead to significant gains over the random walk for the whole or a large part of the forecast horizon in the sectors of information and communication, financial services and real estate activities. The constrained combination forecasts are more accurate than the unconstrained for the entire horizon in the case of information and communication and for the middle of the horizon in the case of financial services. Constrained forecasts for the sector of real estate activities seem to be inferior for short horizons. For the remaining services, the constrained models result in significant gains over the random walk as well as in improved performance over the unconstrained models for one- to four-quarter ahead forecasts. The constrained forecasts for import duties and VAT have significantly higher precision than the benchmark forecasts for mid-horizon; the forecast error of the constrained forecasts is lower than that of the unconstrained for horizons longer than three quarters, but the opposite holds for one- to three-quarter ahead forecasts.

TABLE 6

RMSFE relative to random walk, growth by component forecasted using constrained models

Forecast horizon (quarters)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Agriculture, forestry and fishing, GVA								
Random walk benchmark, RMSFE	8.83	9.16	9.12	10.77	11.00	11.17	11.30	11.72
Predictors as in univariate GDP growth models								
AR(AIC)	1.04	1.23	1.31	1.06	1.05	1.05	1.06	1.05
AR(BIC)	1.03	1.06	1.15	1.04	1.08	1.02	1.02	1.02
AR(1)	1.07	1.05	1.03	1.20	1.04	1.05	1.06	1.05
AR(4)	1.23	1.32	1.58	1.55	1.34	1.18	1.16	1.09
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	1.06	1.22	1.28	1.19	1.19	1.14	1.15	1.13
Mean	1.04	1.20	1.26	1.18	1.17	1.12	1.14	1.12
Trimmed mean (5% trimming)	1.04	1.20	1.26	1.17	1.16	1.12	1.14	1.13
Discounted MSFE (0.90)	1.06	1.17	1.50	1.18	1.17	1.12	1.13	1.13
Discounted MSFE (0.95)	1.06	1.18	1.50	1.18	1.17	1.12	1.13	1.13
Discounted MSFE (1.00)	1.06	1.18	1.49	1.18	1.17	1.12	1.14	1.13
Squared discounted MSFE (0.90)	1.08	1.13	1.80	1.23	1.20	1.12	1.13	1.15
Squared discounted MSFE (0.95)	1.07	1.15	1.79	1.22	1.20	1.12	1.13	1.15
Squared discounted MSFE (1.00)	1.07	1.16	1.78	1.22	1.20	1.12	1.13	1.15
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	1.06	1.23	1.28	1.23	1.21	1.16	1.17	1.14
Mean	1.05	1.21	1.26	1.21	1.19	1.13	1.15	1.13
Trimmed mean (5% trimming)	1.04	1.21	1.26	1.20	1.18	1.13	1.15	1.14
Discounted MSFE (0.90)	1.06	1.18	1.26	1.22	1.19	1.13	1.14	1.14
Discounted MSFE (0.95)	1.06	1.19	1.26	1.22	1.19	1.14	1.15	1.14
Discounted MSFE (1.00)	1.06	1.19	1.25	1.21	1.19	1.14	1.15	1.14
Squared discounted MSFE (0.90)	1.08	1.14	1.28	1.25	1.23	1.14	1.14	1.15
Squared discounted MSFE (0.95)	1.08	1.15	1.26	1.24	1.23	1.14	1.14	1.15
Squared discounted MSFE (1.00)	1.07	1.16	1.25	1.23	1.22	1.14	1.15	1.16
2. Industry, GVA								
Random walk benchmark, RMSFE	1.42	2.55	3.69	4.91	5.02	5.04	5.24	5.46
Predictors as in univariate GDP growth models								
AR(AIC)	0.98	0.98	0.97	1.01	1.02	1.04	1.04	1.08
AR(BIC)	0.96	0.96	0.97	1.00	1.03	1.03	1.03	1.05
AR(1)	**0.95**	0.98	0.97	1.00	1.04	1.03	1.05	1.07
AR(4)	0.99	1.00	1.02	1.08	1.13	1.20	1.24	1.30
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.94**	**0.92**	0.93	0.97	1.00	1.03	1.04	1.08
Mean	**0.93**	**0.90**	0.91	0.95	0.99	1.02	1.03	1.08
Trimmed mean (5% trimming)	**0.93**	**0.91**	0.92	0.96	1.00	1.02	1.03	1.07
Discounted MSFE (0.90)	**0.92**	**0.90**	0.91	0.95	0.99	1.02	1.04	1.08
Discounted MSFE (0.95)	**0.92**	**0.90**	0.91	0.95	0.99	1.02	1.04	1.08
Discounted MSFE (1.00)	**0.92**	**0.90**	0.91	0.95	0.99	1.02	1.04	1.07
Squared discounted MSFE (0.90)	**0.91**	0.90	0.91	0.95	0.98	1.02	1.05	1.09
Squared discounted MSFE (0.95)	**0.91**	0.90	0.91	0.95	0.98	1.03	1.05	1.08
Squared discounted MSFE (1.00)	**0.92**	0.90	0.92	0.95	0.98	1.03	1.04	1.08
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.93**	**0.91**	0.92	0.97	1.00	1.04	1.06	1.09
Mean	**0.92**	**0.89**	0.90	0.95	0.98	1.02	1.04	1.08
Trimmed mean (5% trimming)	**0.92**	**0.90**	0.92	0.96	1.00	1.02	1.04	1.07
Discounted MSFE (0.90)	**0.91**	**0.89**	0.90	0.94	0.97	1.02	1.04	1.08
Discounted MSFE (0.95)	**0.91**	**0.89**	0.91	0.94	0.98	1.02	1.04	1.08
Discounted MSFE (1.00)	**0.91**	**0.89**	0.91	0.94	0.98	1.02	1.04	1.08
Squared discounted MSFE (0.90)	**0.90**	**0.88**	0.90	0.94	0.97	1.02	1.05	1.09
Squared discounted MSFE (0.95)	**0.90**	**0.89**	0.91	0.94	0.97	1.02	1.05	1.09
Squared discounted MSFE (1.00)	**0.90**	**0.89**	0.91	0.94	0.97	1.02	1.05	1.09
3. Construction, GVA								
Random walk benchmark, RMSFE	6.19	9.78	13.95	18.69	19.51	20.32	21.32	22.41
Predictors as in univariate GDP growth models								
AR(AIC)	**0.81**	**0.74**	**0.76**	0.80	0.86	0.94	0.94	1.01
AR(BIC)	**0.84**	**0.74**	**0.76**	0.84	0.93	1.02	**0.99**	0.98
AR(1)	**0.91**	**0.85**	**0.79**	0.85	0.88	0.92	0.93	0.96
AR(4)	**0.80**	**0.76**	**0.76**	0.83	0.91	0.98	0.99	1.05
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.83**	**0.74**	**0.76**	0.80	0.87	0.92	0.91	0.95
Mean	**0.82**	**0.72**	**0.74**	0.79	0.85	0.91	0.90	0.95
Trimmed mean (5% trimming)	**0.81**	**0.72**	**0.74**	0.80	0.86	0.92	0.91	0.96
Discounted MSFE (0.90)	**0.81**	**0.71**	**0.74**	0.79	0.86	0.91	0.91	0.96
Discounted MSFE (0.95)	**0.81**	**0.71**	**0.74**	0.79	0.86	0.91	0.91	0.95
Discounted MSFE (1.00)	**0.81**	**0.72**	**0.74**	0.79	0.86	0.91	0.91	0.95
Squared discounted MSFE (0.90)	**0.80**	**0.72**	**0.74**	0.80	0.86	0.92	0.93	0.98
Squared discounted MSFE (0.95)	**0.81**	**0.72**	**0.74**	0.80	0.86	0.92	0.92	0.97
Squared discounted MSFE (1.00)	**0.81**	**0.72**	**0.74**	0.80	0.86	0.92	0.92	0.96
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.83**	**0.73**	**0.75**	0.79	0.86	0.91	0.91	0.95
Mean	**0.82**	**0.72**	**0.74**	0.77	0.83	0.89	0.89	0.94
Trimmed mean (5% trimming)	**0.82**	**0.72**	**0.74**	0.79	0.85	0.91	0.91	0.95
Discounted MSFE (0.90)	**0.81**	**0.71**	**0.74**	0.77	0.83	0.89	0.89	0.95
Discounted MSFE (0.95)	**0.81**	**0.71**	**0.74**	0.77	0.84	0.89	0.89	0.95
Discounted MSFE (1.00)	**0.81**	**0.71**	**0.74**	0.77	0.84	0.89	0.89	0.94
Squared discounted MSFE (0.90)	**0.80**	**0.70**	**0.73**	0.78	0.83	0.88	0.90	0.96
Squared discounted MSFE (0.95)	**0.80**	**0.71**	**0.74**	0.78	0.83	0.89	0.91	0.96
Squared discounted MSFE (1.00)	**0.81**	**0.71**	**0.74**	0.78	0.84	0.89	0.90	0.95

TABLE 6 (continued)

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
4. Trade, transport, accommodation & food services, GVA								
Random walk benchmark, RMSFE	1.44	2.49	3.59	4.86	5.19	5.45	5.70	6.00
Predictors as in univariate GDP growth models								
AR(AIC)	**0.91**	0.88	**0.85**	**0.87**	**0.89**	**0.92**	**0.92**	**0.95**
AR(BIC)	**0.88**	0.86	**0.85**	**0.90**	**0.93**	**0.97**	0.96	0.96
AR(1)	**0.89**	**0.86**	**0.86**	**0.91**	**0.91**	**0.93**	**0.94**	**0.95**
AR(4)	**0.87**	0.86	**0.86**	0.90	0.94	0.99	1.00	1.02
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.74**	**0.70**	**0.72**	**0.79**	**0.86**	0.92	0.94	0.96
Mean	**0.73**	**0.68**	**0.70**	**0.77**	**0.84**	0.91	0.93	0.96
Trimmed mean (5% trimming)	**0.73**	**0.69**	**0.72**	**0.79**	**0.86**	0.92	0.94	0.97
Discounted MSFE (0.90)	**0.70**	**0.68**	**0.70**	**0.76**	**0.83**	0.91	0.93	0.97
Discounted MSFE (0.95)	**0.71**	**0.68**	**0.70**	**0.77**	**0.83**	0.91	0.93	0.97
Discounted MSFE (1.00)	**0.71**	**0.68**	**0.70**	**0.77**	**0.84**	0.91	0.93	0.97
Squared discounted MSFE (0.90)	**0.70**	**0.68**	**0.71**	**0.76**	0.82	0.91	0.93	0.98
Squared discounted MSFE (0.95)	**0.71**	**0.67**	**0.71**	**0.76**	0.82	0.91	0.93	0.98
Squared discounted MSFE (1.00)	**0.71**	**0.67**	**0.71**	**0.76**	0.83	0.92	0.93	0.97
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.72**	**0.67**	**0.69**	**0.76**	**0.84**	0.92	0.94	0.97
Mean	**0.71**	**0.65**	**0.68**	**0.75**	**0.82**	0.89	0.92	0.95
Trimmed mean (5% trimming)	**0.71**	**0.67**	**0.69**	**0.77**	**0.84**	0.91	0.93	0.97
Discounted MSFE (0.90)	**0.69**	**0.66**	**0.67**	**0.74**	**0.81**	0.89	0.92	0.96
Discounted MSFE (0.95)	**0.69**	**0.66**	**0.67**	**0.74**	**0.81**	0.89	0.92	0.96
Discounted MSFE (1.00)	**0.69**	**0.66**	**0.67**	**0.74**	**0.81**	0.89	0.92	0.96
Squared discounted MSFE (0.90)	**0.68**	**0.64**	**0.66**	**0.73**	0.79	0.88	0.92	0.97
Squared discounted MSFE (0.95)	**0.69**	**0.64**	**0.66**	**0.74**	0.80	0.89	0.92	0.97
Squared discounted MSFE (1.00)	**0.69**	**0.64**	**0.66**	**0.74**	0.81	0.89	0.93	0.97
5. Information and communication, GVA								
Random walk benchmark, RMSFE	3.40	5.52	7.63	9.41	9.87	9.65	9.24	9.77
Predictors as in univariate GDP growth models								
AR(AIC)	**0.94**	**0.87**	**0.85**	**0.75**	**0.72**	**0.67**	**0.69**	**0.71**
AR(BIC)	**0.92**	**0.88**	**0.85**	**0.75**	**0.73**	**0.71**	**0.72**	**0.72**
AR(1)	**0.91**	**0.86**	**0.83**	**0.75**	**0.73**	**0.69**	**0.69**	**0.71**
AR(4)	**0.93**	**0.87**	**0.86**	**0.78**	**0.78**	**0.77**	**0.79**	**0.79**
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.92**	**0.87**	**0.85**	**0.76**	**0.74**	**0.72**	**0.73**	**0.74**
Mean	**0.90**	**0.85**	**0.83**	**0.75**	**0.73**	**0.70**	**0.72**	**0.73**
Trimmed mean (5% trimming)	**0.90**	**0.85**	**0.83**	**0.75**	**0.73**	**0.70**	**0.71**	**0.73**
Discounted MSFE (0.90)	**0.90**	**0.85**	**0.86**	**0.73**	**0.73**	**0.69**	**0.71**	**0.72**
Discounted MSFE (0.95)	**0.90**	**0.85**	**0.86**	**0.73**	**0.73**	**0.69**	**0.71**	**0.73**
Discounted MSFE (1.00)	**0.90**	**0.85**	**0.86**	**0.74**	**0.73**	**0.69**	**0.71**	**0.73**
Squared discounted MSFE (0.90)	**0.90**	**0.84**	0.89	**0.72**	**0.74**	**0.67**	**0.69**	**0.71**
Squared discounted MSFE (0.95)	**0.90**	**0.84**	0.89	**0.73**	**0.75**	**0.67**	**0.70**	**0.72**
Squared discounted MSFE (1.00)	**0.90**	**0.84**	0.89	**0.73**	**0.75**	**0.67**	**0.70**	**0.72**
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.92**	**0.87**	**0.85**	**0.77**	**0.76**	**0.73**	**0.74**	**0.74**
Mean	**0.91**	**0.85**	**0.84**	**0.75**	**0.74**	**0.70**	**0.72**	**0.73**
Trimmed mean (5% trimming)	**0.90**	**0.86**	**0.84**	**0.75**	**0.74**	**0.70**	**0.72**	**0.72**
Discounted MSFE (0.90)	**0.90**	**0.86**	**0.83**	**0.74**	**0.74**	**0.69**	**0.71**	**0.72**
Discounted MSFE (0.95)	**0.91**	**0.86**	**0.83**	**0.75**	**0.74**	**0.69**	**0.71**	**0.72**
Discounted MSFE (1.00)	**0.91**	**0.86**	**0.83**	**0.75**	**0.74**	**0.69**	**0.71**	**0.73**
Squared discounted MSFE (0.90)	**0.90**	**0.86**	**0.81**	**0.74**	**0.75**	**0.69**	**0.69**	**0.71**
Squared discounted MSFE (0.95)	**0.90**	**0.86**	**0.82**	**0.75**	**0.75**	**0.69**	**0.70**	**0.71**
Squared discounted MSFE (1.00)	**0.90**	**0.86**	**0.82**	**0.75**	**0.76**	**0.69**	**0.71**	**0.72**
6. Financial and insurance activities, GVA								
Random walk benchmark, RMSFE	2.53	4.47	6.37	8.32	8.65	9.01	9.37	9.80
Predictors as in univariate GDP growth models								
AR(AIC)	**0.76**	**0.71**	**0.70**	**0.66**	**0.66**	**0.68**	**0.71**	**0.74**
AR(BIC)	**0.77**	**0.73**	**0.69**	**0.68**	**0.73**	**0.79**	**0.82**	**0.81**
AR(1)	**0.80**	**0.75**	**0.74**	**0.72**	**0.72**	**0.71**	**0.74**	**0.75**
AR(4)	**0.73**	**0.69**	**0.66**	**0.63**	**0.63**	**0.65**	**0.69**	**0.72**
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.76**	**0.72**	**0.69**	**0.67**	**0.69**	**0.71**	**0.75**	**0.77**
Mean	**0.74**	**0.70**	**0.68**	**0.65**	**0.67**	**0.70**	**0.74**	**0.76**
Trimmed mean (5% trimming)	**0.74**	**0.70**	**0.67**	**0.65**	**0.67**	**0.70**	**0.74**	**0.77**
Discounted MSFE (0.90)	**0.76**	**0.70**	**0.68**	**0.66**	**0.67**	**0.70**	**0.73**	**0.76**
Discounted MSFE (0.95)	**0.76**	**0.70**	**0.69**	**0.66**	**0.67**	**0.70**	**0.73**	**0.76**
Discounted MSFE (1.00)	**0.76**	**0.71**	**0.69**	**0.66**	**0.67**	**0.70**	**0.73**	**0.76**
Squared discounted MSFE (0.90)	**0.75**	**0.71**	**0.70**	0.71	**0.66**	**0.72**	**0.72**	**0.75**
Squared discounted MSFE (0.95)	**0.75**	**0.71**	**0.70**	0.71	**0.66**	**0.72**	**0.72**	**0.76**
Squared discounted MSFE (1.00)	**0.75**	**0.72**	**0.71**	0.71	**0.67**	**0.73**	**0.73**	**0.76**
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.75**	**0.73**	**0.69**	**0.67**	**0.69**	**0.72**	**0.75**	**0.77**
Mean	**0.74**	**0.71**	**0.68**	**0.65**	**0.66**	**0.69**	**0.73**	**0.76**
Trimmed mean (5% trimming)	**0.74**	**0.70**	**0.68**	**0.65**	**0.66**	**0.70**	**0.73**	**0.76**
Discounted MSFE (0.90)	**0.76**	**0.71**	**0.69**	**0.66**	**0.66**	**0.69**	**0.72**	**0.75**
Discounted MSFE (0.95)	**0.76**	**0.71**	**0.69**	**0.66**	**0.66**	**0.69**	**0.73**	**0.75**
Discounted MSFE (1.00)	**0.76**	**0.71**	**0.69**	**0.66**	**0.66**	**0.70**	**0.73**	**0.76**
Squared discounted MSFE (0.90)	**0.74**	**0.71**	**0.70**	**0.67**	**0.66**	**0.69**	**0.71**	**0.75**
Squared discounted MSFE (0.95)	**0.74**	**0.71**	**0.70**	**0.67**	**0.66**	**0.70**	**0.72**	**0.75**
Squared discounted MSFE (1.00)	**0.75**	**0.72**	**0.70**	**0.67**	**0.66**	**0.70**	**0.72**	**0.76**

TABLE 6 (continued)

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
7. Real estate activities, GVA								
Random walk benchmark, RMSFE	0.51	1.04	1.57	2.13	2.23	2.33	2.42	2.54
Predictors as in univariate GDP growth models								
AR(AIC)	**0.70**	**0.75**	**0.78**	**0.78**	**0.81**	**0.84**	**0.83**	0.84
AR(BIC)	**0.72**	**0.77**	**0.78**	**0.79**	**0.85**	**0.91**	**0.93**	0.91
AR(1)	**0.76**	**0.81**	**0.82**	**0.83**	**0.85**	**0.87**	**0.87**	0.87
AR(4)	**0.71**	**0.75**	**0.76**	**0.74**	**0.77**	**0.78**	**0.78**	0.79
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.71**	**0.73**	**0.72**	**0.73**	**0.80**	**0.83**	0.84	0.85
Mean	**0.70**	**0.71**	**0.71**	**0.72**	**0.78**	**0.82**	0.83	0.85
Trimmed mean (5% trimming)	**0.70**	**0.71**	**0.72**	**0.73**	**0.79**	**0.83**	0.84	0.86
Discounted MSFE (0.90)	**0.69**	**0.71**	**0.70**	**0.72**	**0.77**	**0.81**	0.83	0.85
Discounted MSFE (0.95)	**0.69**	**0.71**	**0.70**	**0.72**	**0.78**	**0.81**	0.83	0.85
Discounted MSFE (1.00)	**0.70**	**0.71**	**0.71**	**0.72**	**0.78**	**0.81**	0.83	0.85
Squared discounted MSFE (0.90)	**0.70**	**0.71**	**0.70**	**0.72**	**0.76**	**0.79**	0.81	0.84
Squared discounted MSFE (0.95)	**0.70**	**0.71**	**0.70**	**0.72**	**0.77**	**0.80**	0.82	0.84
Squared discounted MSFE (1.00)	**0.71**	**0.71**	**0.71**	**0.72**	**0.77**	**0.81**	0.82	0.84
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.71**	**0.73**	**0.72**	**0.73**	**0.79**	**0.83**	0.84	0.85
Mean	**0.70**	**0.71**	**0.70**	**0.71**	**0.77**	**0.81**	0.82	0.84
Trimmed mean (5% trimming)	**0.70**	**0.71**	**0.71**	**0.73**	**0.79**	**0.83**	0.84	0.85
Discounted MSFE (0.90)	**0.69**	**0.71**	**0.70**	**0.71**	**0.76**	**0.80**	0.82	0.84
Discounted MSFE (0.95)	**0.69**	**0.71**	**0.70**	**0.71**	**0.76**	**0.80**	0.82	0.84
Discounted MSFE (1.00)	**0.70**	**0.71**	**0.70**	**0.71**	**0.77**	**0.80**	0.82	0.84
Squared discounted MSFE (0.90)	**0.70**	**0.70**	**0.70**	**0.70**	**0.75**	**0.77**	0.80	0.83
Squared discounted MSFE (0.95)	**0.71**	**0.71**	**0.70**	**0.70**	**0.75**	**0.79**	0.81	0.83
Squared discounted MSFE (1.00)	**0.71**	**0.71**	**0.70**	**0.71**	**0.76**	**0.79**	0.82	0.84
8. Professional and administrative activities, GVA								
Random walk benchmark, RMSFE	1.80	3.05	4.22	5.13	5.23	5.38	5.49	5.50
Predictors as in univariate GDP growth models								
AR(AIC)	0.98	1.02	1.00	0.94	0.94	0.95	0.95	**0.95**
AR(BIC)	**0.94**	0.99	0.98	0.93	0.94	0.95	0.96	**0.96**
AR(1)	0.96	0.94	0.96	0.94	0.94	0.96	0.97	0.97
AR(4)	0.98	1.02	1.05	1.01	1.02	1.03	1.04	1.04
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	0.96	0.98	0.97	0.92	**0.94**	0.96	0.98	1.00
Mean	0.95	0.96	0.96	0.91	**0.93**	0.95	0.97	1.00
Trimmed mean (5% trimming)	0.95	0.97	0.96	0.91	**0.92**	0.94	0.96	0.99
Discounted MSFE (0.90)	0.95	0.95	0.93	0.90	**0.92**	0.94	0.97	1.00
Discounted MSFE (0.95)	0.95	0.95	0.93	0.90	**0.92**	0.94	0.97	1.00
Discounted MSFE (1.00)	0.94	0.95	0.93	0.90	**0.92**	0.94	0.97	1.00
Squared discounted MSFE (0.90)	0.94	0.95	0.92	0.92	**0.91**	0.95	0.97	1.00
Squared discounted MSFE (0.95)	**0.94**	0.95	0.91	0.93	**0.91**	0.95	0.97	1.00
Squared discounted MSFE (1.00)	**0.94**	0.94	0.91	0.93	**0.91**	0.96	0.97	1.00
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.95**	0.97	0.97	0.92	**0.95**	0.97	0.99	1.02
Mean	**0.94**	0.96	0.95	0.91	**0.93**	0.95	0.97	1.00
Trimmed mean (5% trimming)	**0.94**	0.96	0.96	0.90	**0.92**	0.94	0.97	0.99
Discounted MSFE (0.90)	0.94	0.94	0.95	0.90	**0.91**	0.94	0.97	1.00
Discounted MSFE (0.95)	**0.94**	0.95	0.95	0.90	**0.91**	0.94	0.97	1.00
Discounted MSFE (1.00)	**0.94**	0.94	0.95	0.90	**0.91**	0.94	0.97	1.00
Squared discounted MSFE (0.90)	**0.94**	0.94	0.96	**0.89**	**0.91**	0.94	0.97	1.01
Squared discounted MSFE (0.95)	**0.94**	0.94	0.96	**0.89**	**0.91**	0.94	0.97	1.01
Squared discounted MSFE (1.00)	**0.93**	0.93	0.95	**0.89**	**0.91**	0.94	0.97	1.01
9. Public administration education and health activities, GVA								
Random walk benchmark, RMSFE	1.60	1.73	2.08	2.75	2.89	2.96	3.10	3.23
Predictors as in univariate GDP growth models								
AR(AIC)	1.06	1.03	0.92	0.82	0.86	0.92	0.90	0.93
AR(BIC)	1.00	1.06	**0.89**	0.84	0.92	1.01	1.01	0.99
AR(1)	1.02	1.01	1.05	0.87	0.92	0.97	0.93	0.96
AR(4)	1.00	0.98	0.89	0.84	0.90	0.93	0.92	0.93
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	1.01	1.07	0.93	0.87	0.94	0.99	0.98	0.98
Mean	1.00	1.05	0.92	0.86	0.93	0.97	0.97	0.97
Trimmed mean (5% trimming)	1.00	1.04	0.91	0.85	0.92	0.98	0.97	0.98
Discounted MSFE (0.90)	0.99	1.06	0.93	0.85	0.92	0.97	0.96	0.97
Discounted MSFE (0.95)	0.99	1.05	0.93	0.85	0.92	0.97	0.97	0.97
Discounted MSFE (1.00)	0.99	1.05	0.93	0.85	0.92	0.97	0.97	0.98
Squared discounted MSFE (0.90)	0.99	1.10	0.94	0.87	0.92	0.98	0.96	0.97
Squared discounted MSFE (0.95)	0.99	1.09	0.94	0.87	0.93	0.99	0.96	0.97
Squared discounted MSFE (1.00)	0.98	1.09	0.94	0.87	0.93	0.99	0.96	0.97
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	1.02	1.07	0.94	0.88	0.96	1.00	0.99	0.99
Mean	1.01	1.05	0.92	0.87	0.93	0.98	0.97	0.98
Trimmed mean (5% trimming)	1.00	1.04	0.92	0.86	0.93	0.98	0.98	0.99
Discounted MSFE (0.90)	1.00	1.05	0.92	0.86	0.93	0.97	0.97	0.98
Discounted MSFE (0.95)	1.00	1.05	0.92	0.86	0.93	0.97	0.97	0.98
Discounted MSFE (1.00)	1.00	1.05	0.92	0.86	0.93	0.98	0.97	0.98
Squared discounted MSFE (0.90)	0.99	1.05	0.93	0.86	0.93	0.97	0.96	0.97
Squared discounted MSFE (0.95)	0.99	1.04	0.93	0.86	0.93	0.97	0.96	0.98
Squared discounted MSFE (1.00)	0.98	1.04	0.93	0.86	0.93	0.97	0.97	0.98

TABLE 6 (continued)

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
10. Other services, GVA								
Random walk benchmark, RMSFE	1.74	3.07	4.54	6.09	6.27	6.50	6.70	6.98
Predictors as in univariate GDP growth models								
AR(AIC)	**0.86**	**0.85**	**0.85**	**0.83**	**0.88**	**0.91**	0.91	0.92
AR(BIC)	**0.86**	**0.84**	**0.85**	**0.84**	**0.91**	**0.95**	0.96	0.95
AR(1)	**0.94**	**0.89**	**0.91**	**0.88**	**0.90**	**0.93**	0.92	0.92
AR(4)	**0.89**	**0.86**	0.87	0.85	0.89	0.92	0.92	0.90
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	**0.86**	**0.84**	**0.85**	0.85	0.91	0.94	0.93	0.92
Mean	**0.85**	**0.82**	**0.83**	**0.84**	0.89	0.92	0.91	0.91
Trimmed mean (5% trimming)	**0.85**	**0.82**	**0.83**	**0.83**	0.89	0.92	0.92	0.92
Discounted MSFE (0.90)	**0.85**	**0.82**	**0.83**	**0.84**	0.90	0.92	0.91	0.91
Discounted MSFE (0.95)	**0.85**	**0.82**	**0.83**	**0.84**	0.90	0.92	0.91	0.91
Discounted MSFE (1.00)	**0.85**	**0.82**	**0.83**	**0.84**	0.89	0.92	0.91	0.91
Squared discounted MSFE (0.90)	**0.85**	**0.83**	**0.84**	0.85	0.90	0.93	0.91	0.91
Squared discounted MSFE (0.95)	**0.85**	**0.83**	**0.83**	0.85	0.90	0.93	0.91	0.91
Squared discounted MSFE (1.00)	**0.85**	**0.83**	**0.83**	0.84	0.90	0.93	0.91	0.91
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	**0.87**	**0.84**	0.85	0.86	0.92	0.95	0.93	0.92
Mean	**0.85**	**0.82**	**0.83**	0.84	0.89	0.92	0.91	0.91
Trimmed mean (5% trimming)	**0.85**	**0.82**	**0.83**	0.83	0.89	0.92	0.91	0.91
Discounted MSFE (0.90)	**0.85**	**0.83**	0.84	0.84	0.90	0.93	0.91	0.91
Discounted MSFE (0.95)	**0.85**	**0.83**	0.83	0.84	0.90	0.93	0.91	0.91
Discounted MSFE (1.00)	**0.85**	**0.83**	**0.83**	0.84	0.90	0.93	0.91	0.91
Squared discounted MSFE (0.90)	**0.85**	**0.84**	0.84	0.85	0.91	0.94	0.91	0.91
Squared discounted MSFE (0.95)	**0.85**	**0.83**	0.84	0.85	0.91	0.93	0.91	0.91
Squared discounted MSFE (1.00)	**0.86**	**0.83**	**0.83**	0.85	0.90	0.93	0.91	0.91
11. Import duties and value added tax								
Random walk benchmark, RMSFE	2.34	3.42	3.99	4.33	4.37	4.62	4.85	5.10
Predictors as in univariate GDP growth models								
AR(AIC)	1.02	0.99	0.93	**0.84**	0.90	0.94	0.94	0.96
AR(BIC)	0.99	0.97	0.92	**0.88**	0.96	1.00	1.00	0.98
AR(1)	1.03	0.96	0.96	**0.87**	0.93	0.93	0.97	0.96
AR(4)	1.03	0.98	0.93	**0.84**	0.92	0.95	0.96	0.98
Forecast combinations								
Predictors as in ADL/FAR/FADL GDP growth models, all predictors								
Median	1.01	0.96	**0.86**	**0.79**	**0.87**	0.93	0.94	0.97
Mean	1.01	0.96	**0.86**	**0.79**	**0.87**	0.93	0.94	0.98
Trimmed mean (5% trimming)	1.01	0.96	**0.86**	**0.79**	**0.88**	0.94	0.94	0.98
Discounted MSFE (0.90)	1.02	0.95	**0.87**	**0.78**	**0.85**	0.92	0.93	0.98
Discounted MSFE (0.95)	1.02	0.95	**0.87**	**0.78**	**0.85**	0.92	0.94	0.98
Discounted MSFE (1.00)	1.02	0.95	**0.87**	**0.78**	**0.86**	0.92	0.94	0.98
Squared discounted MSFE (0.90)	1.02	0.94	0.89	**0.77**	**0.83**	0.92	0.93	0.98
Squared discounted MSFE (0.95)	1.02	0.94	0.89	**0.78**	**0.84**	0.92	0.94	0.98
Squared discounted MSFE (1.00)	1.02	0.94	0.89	**0.78**	**0.85**	0.93	0.94	0.98
Predictors as in ADL/FAR/FADL GDP growth models, pre-selected predictors								
Median	1.01	0.96	**0.85**	**0.77**	**0.85**	**0.91**	0.92	0.97
Mean	1.01	0.96	**0.85**	**0.77**	**0.85**	0.91	0.93	0.97
Trimmed mean (5% trimming)	1.01	0.95	**0.85**	**0.78**	**0.87**	0.93	0.94	0.98
Discounted MSFE (0.90)	1.02	0.95	**0.84**	**0.76**	**0.83**	0.90	0.92	0.97
Discounted MSFE (0.95)	1.02	0.95	**0.84**	**0.76**	**0.83**	0.90	0.93	0.97
Discounted MSFE (1.00)	1.02	0.95	**0.84**	**0.76**	**0.84**	0.91	0.93	0.97
Squared discounted MSFE (0.90)	1.02	0.94	**0.84**	**0.75**	**0.80**	0.88	0.92	0.98
Squared discounted MSFE (0.95)	1.02	0.94	**0.84**	**0.76**	**0.81**	0.89	0.93	0.98
Squared discounted MSFE (1.00)	1.02	0.94	**0.84**	**0.76**	**0.82**	0.90	0.93	0.98

Notes: Entries in bold denote statistical significance at 10% level of the modified Diebold-Mariano test of equal forecast accuracy (Diebold and Mariano 1995; Harvey et al. 1997). The tests compare the forecast errors from the benchmark model (random walk) to those from the methods shown in the table.

AR(AIC) and AR(BIC) denote the autoregressive terms selected in the GDP growth models using the Akaike and Bayesian information criteria, respectively; the same GDP growth autoregressive terms as in the GDP growth models are also included in the constrained component models. AR(1) and AR(4) denote the autoregressive terms in the GDP growth models of order one and four, respectively; the same GDP growth autoregressive terms as in the GDP growth models are also included in the constrained component models.

For discounted and squared discounted MSFE forecast combination methods the discount factor is given in parentheses.

Overall, the results show that the constrained growth forecasts for the production-side components, in particular constrained forecast combinations based on discounted MSFE methods, lead to gains over both the random walk benchmark and the unconstrained forecasts in the sectors of construction, trade, transport, accommodation and food services, information and communication, and other services. In the sectors of agriculture, public administration, education and health, and professional services, neither the unconstrained models nor the constrained sectoral models significantly improve on the naïve benchmark.

For the remaining sectors except industry, the performance of the constrained and unconstrained forecasts varies over the horizon thus it is difficult to favour one approach over the other.

5.3 Forecast stability

Figures 2 and 3 juxtapose GDP growth forecasts from the direct and bottom-up approaches, focusing on forecasts based on all the predictors in the dataset and combined through the squared discounted MSFE method. In general, discounted MSFE methods are found to perform well in the forecasting exercises discussed in the previous sections. The corresponding component forecasts for key sectors of the economy are also plotted. More specifically, the constrained component forecasts add up to the GDP growth forecasts computed using the direct approach, while the unconstrained component forecasts add up to the GDP growth forecasts from the bottom-up approach.

One-quarter ahead forecasts from the two approaches are almost indistinguishable; both approaches result in some over-prediction during downturns, particularly in the sectors of construction and industry. The differences between the forecasts generated by the two approaches become larger as the horizon becomes longer. The over-prediction during the period 2008 - 2013 is more pronounced for four-quarter ahead forecasts. For a horizon of four quarters, GDP growth forecasts from the direct approach capture the downturn better than those computed from the bottom-up approach; however during the recent recovery bottom-up growth forecasts have become less imprecise. Across components, the accuracy of four-quarter ahead forecasts exhibits some variation over the economic cycle and does not favour one approach over the other. For example, the recent recovery is predicted more accurately by the unconstrained forecasts for industry computed under the bottom up approach. Differences between the two approaches in terms of performance are less clear in the trade and financial sectors. In the sectors of construction and professional services, the recession is better predicted by constrained forecasts obtained through the direct approach to GDP growth forecasting.

As there are indications that forecast accuracy could change over the economic cycle, the stability of the performance of the two approaches is examined, following Stock and Watson (2004). The pseudo out-of-sample forecast period of 2002Q2 – 2016Q1 was divided in two sub-periods i.e. up to 2008Q4-*h* and from 2009Q1-*h* onwards. The choice of the split date was guided by evidence of a break in actual data for GDP growth and its components in 2008.[19] The relative RMSFEs of GDP growth and component forecasts from the two approaches are computed over the two sub-periods. We focus on forecasts from univariate models, and combination methods incorporating information from the full dataset.

[19] Due to the small sample size associated with the pseudo out-of-sample period we consider only horizons of up to four quarters.

FIGURE 2

One-quarter ahead growth forecasts (y-o-y percentage change)

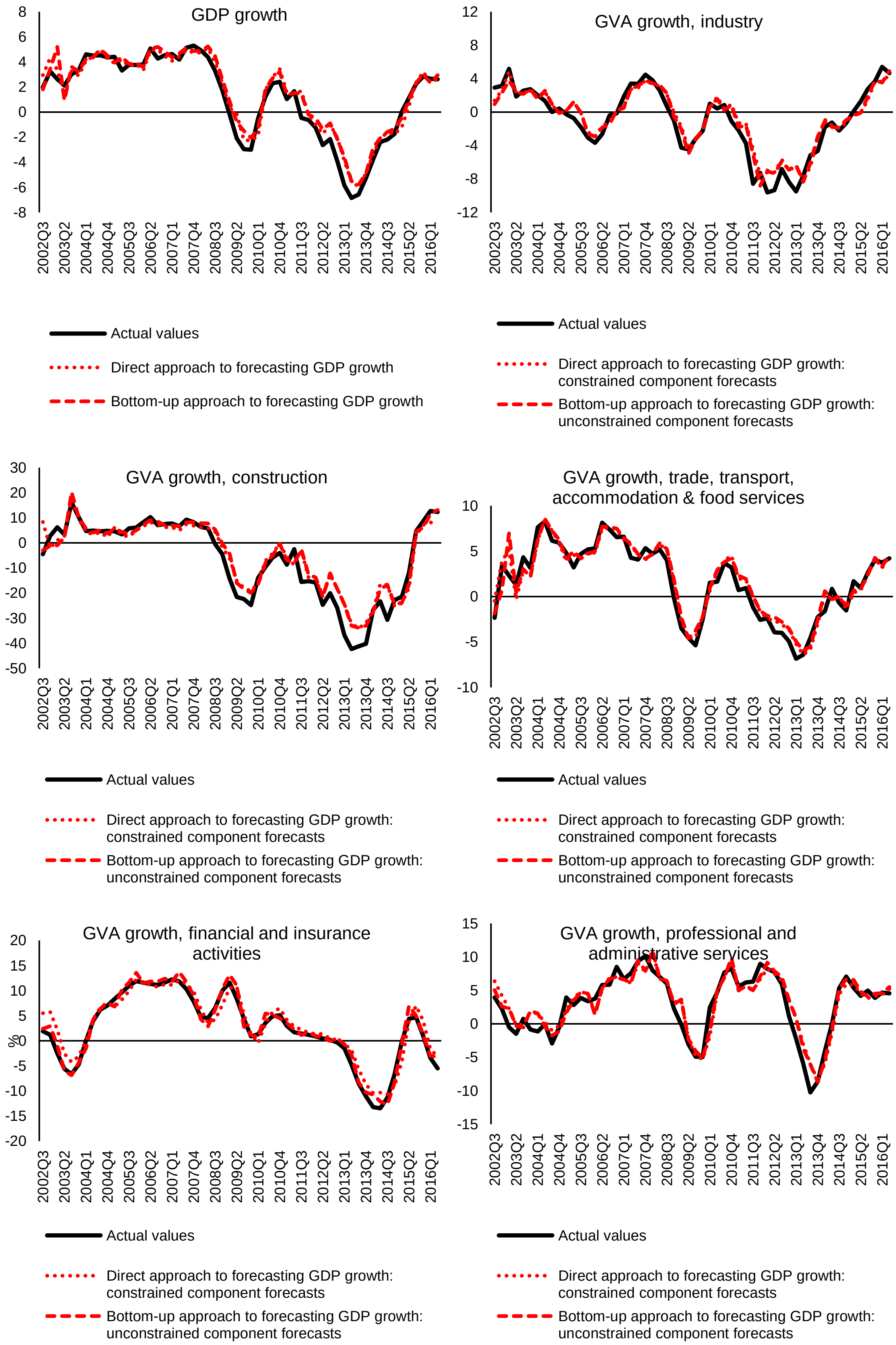


FIGURE 3

Four-quarter ahead growth forecasts (y-o-y percentage change)

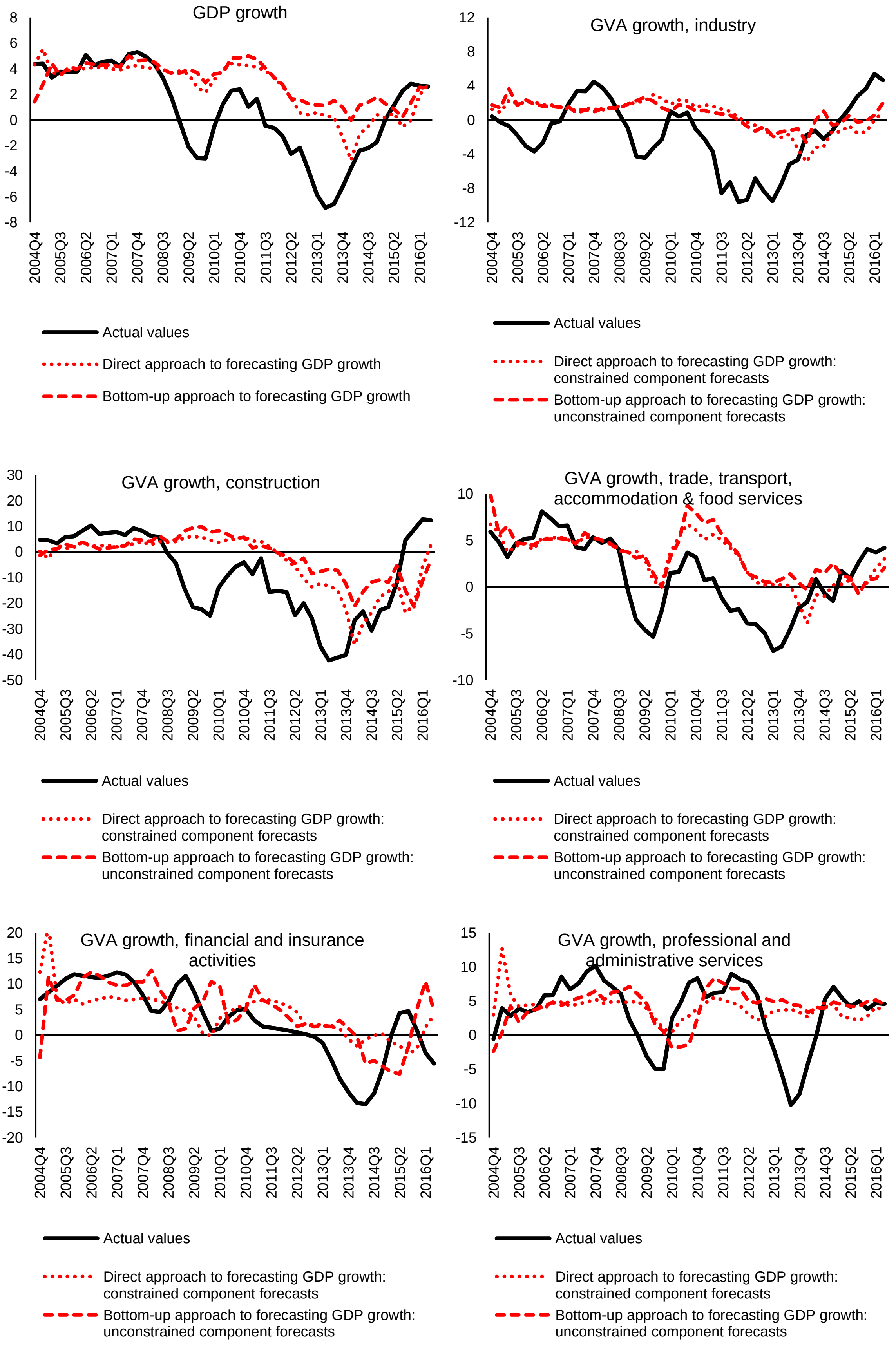


Table 7 presents the average relative RMSFEs in the two sub-periods for different univariate forecasts and forecast combinations; the table also reports the average absolute difference between the relative RMSFEs in the two sub-periods. The average is computed across the 12 variables forecasted (GDP and 11 production-side components) and four horizons.

There is some evidence of instability as in the first period the forecasts are, on average, at least as accurate as the naïve forecasts in most cases, while in the second period the forecasts based on univariate models or forecast combinations outperform the naïve forecasts in all cases. Simple forecast combinations and discounted MSFE combinations under the direct approach outperform the random walk benchmark marginally in the first period and improve further on the benchmark in the second period. Under the bottom-up approach, only the simple AR(1) model outperforms the random walk in both periods. The average absolute difference in the relative performance between the two periods is more dispersed for univariate models than for forecast combinations. Squared discounted MSFE forecast combinations computed under the direct approach exhibit the largest absolute change among combination methods. Discounted MSFE methods under the bottom-up approach are associated with the smallest average relative RMSFEs in the second period; they also have smaller average absolute changes in relative RMSFEs from one period to the next vis-à-vis other combination methods under either approach of forecasting GDP growth.

The results of Table 7 reflect also the effects of the short time series span available for quarterly analysis in Cyprus. The higher average relative RMSFEs in the first period as well as the fact that simple AR(1) models produce the smallest average absolute change between the two periods, could reflect, in addition to instability, higher estimation uncertainty in the first period.

TABLE 7

Stability of forecasts from the direct and bottom-up approaches

	2002Q2 to 2008Q4-*h*	**2009Q1-*h* to 2016Q1**	**Mean absolute difference between relative RMSFEs in the two periods**
	RMSFEs relative to RW, mean	**RMSFEs relative to RW, mean**	
Direct approach to forecasting GDP growth: constrained component forecasts			
Univariate forecasts			
AR(AIC)	1.01	0.90	0.22
AR(BIC)	1.00	0.87	0.18
AR(1)	1.00	0.91	0.17
AR(4)	1.02	0.97	0.30
Forecast combinations			
Median	0.98	0.87	0.23
Mean	0.98	0.86	0.24
Trimmed mean (5% trimming)	0.98	0.86	0.23
Discounted MSFE (0.90)	0.98	0.86	0.25
Discounted MSFE (0.95)	0.98	0.86	0.24
Discounted MSFE (1.00)	0.98	0.86	0.24
Squared discounted MSFE (0.90)	1.01	0.87	0.28
Squared discounted MSFE (0.95)	1.01	0.88	0.28
Squared discounted MSFE (1.00)	1.01	0.88	0.28
Bottom-up approach to forecasting GDP growth: unconstrained component forecasts			
Univariate forecasts			
AR(AIC)	1.07	0.87	0.26
AR(BIC)	1.08	0.88	0.23
AR(1)	0.97	0.87	0.13
AR(4)	1.08	0.86	0.29
Forecast combinations			
Median	1.05	0.84	0.25
Mean	1.04	0.84	0.25
Trimmed mean (5% trimming)	1.04	0.84	0.25
Discounted MSFE (0.90)	1.02	0.84	0.23
Discounted MSFE (0.95)	1.02	0.84	0.23
Discounted MSFE (1.00)	1.02	0.84	0.23
Squared discounted MSFE (0.90)	1.04	0.84	0.25
Squared discounted MSFE (0.95)	1.04	0.84	0.25
Squared discounted MSFE (1.00)	1.04	0.85	0.25

Note: The number of observations for the computation of the summary statistics is 48.

6. Summary and conclusions

The systematic analysis of the developments and outlook for different sectors of the Cypriot economy is highly relevant for uncovering the changes in the sectoral structure of the economy and for determining the activities that will drive future growth. The development of reliable models at sector level is faced with data limitations, particularly in some sectors of activity for which the number of relevant predictors is small. In this paper, we use an extensive dataset of over 300 aggregate and sectoral indicators, covering both the domestic economy and external economic conditions, to construct short-term forecasts for sectoral and aggregate activity.

We estimate single equation dynamic models and compute forecast combinations for forecasting GDP growth as well as the growth rate of all the components that appear on the production side of the quarterly national accounts, namely the GVA (constant prices) in 10 sectors and import duties plus VAT. Aggregate and component forecasts are computed under two approaches to forecasting GDP growth, namely a direct and a bottom-up approach. In the direct approach, unconstrained models for GDP growth are estimated to compute forecasts for the aggregate, while constrained component models are used to obtain the disaggregate forecasts which add up to the GDP growth forecasts computed directly. In the bottom-up approach, unconstrained component models are estimated to compute growth forecasts for the components as well as for GDP growth by adding up the unconstrained component forecasts. The performance of aggregate and disaggregate forecasts from the two approaches is assessed via pseudo out-of-sample exercises.

The results of the analysis show that information from macroeconomic and financial predictors improves on the accuracy of the naïve forecasts for most production-side components and the aggregate, under both the direct and bottom-up approaches. Statistically significant gains over the benchmark are found mainly for horizons of up to four quarters; significant forecast gains are also found for longer horizons for some components under the direct approach. GDP growth forecasts from the direct approach are somewhat superior to those from the bottom-up approach. Forecast gains over the random walk benchmark are as high as 35% and 30% under the direct approach and bottom-up approach, respectively.

Looking at the components, unconstrained growth forecasts for industry, construction, trade, real estate activities and import duties, lead to significant gains for short horizons, while for financial activities gains occur early on and at the end of the horizon. Component forecast gains under the bottom-up approach range from as high as 50% for the financial and trade sector to 10% for industry. Constrained component forecasts lead to improved accuracy over naïve forecasts for short to medium horizons in the case of industry, construction trade, real estate activities, other services and import duties. Moreover, constrained growth forecasts for the sectors of financial activities, and information and communication outperform the benchmark throughout the forecast horizon. For constrained component forecasts the highest gains are achieved in financial and trade sectors (about 30%), while the smallest gains are registered in the industry sector (about 10%). Compared to the unconstrained component forecasts, gains attained through constrained component forecasts are slightly lower, but more widespread across components and horizons. In the sector of professional services gains are limited for both constrained and unconstrained forecasts. In the sectors of agriculture and public administration, education and health neither, the unconstrained sectoral models nor the constrained models significantly improve on the naïve benchmark.

Another result of the analysis is that aggregate and disaggregate forecasts computed from a set of pre-selected predictors which are highly correlated with the dependent variables are at least as accurate as the forecasts obtained using the full set of predictors. This result could be explored further in future research using more sophisticated pre-selection techniques (e.g. regularisation methods). Moreover, the results revealed some forecast instability although the pseudo out-of-sample period here is much smaller compared to other similar stability exercises (e.g. Stock and Watson 2003, 2004). The investigation of forecast stability could be addressed further in future work by expanding the model space for forecast combinations.

This paper extends the methodology currently used at the Economics Research Centre for forecasting GDP growth to the construction of forecasts for the production side of the national accounts. The analysis in this paper provides indications in favour of the direct approach to forecasting GDP growth. However, the results also point towards some instability in the forecasting performance. For example, during the recent recession the direct approach produced less imprecise forecasts for GDP growth and for most of its components than the bottom-up approach, but the opposite seems to have occurred during the subsequent recovery. As the available time series span is relatively short, with only one major recession episode, the accuracy of aggregate and disaggregate forecasts from both the direct and bottom-up approaches should be systematically monitored.

The methods employed in this paper can also be applied in the construction of forecasts for the expenditure components of GDP, thereby developing a full set of tools for identifying growth drivers in the Cypriot economy, from both the supply and demand sides. Another extension of this work is to explore systems of equations in which the dynamic interrelations among production-side components can be modelled directly. The dominance of naïve forecasts in some sectors, in terms of accuracy, found in this paper, could guide the choice of statistical restrictions on systems of equations for components. Systems can be used for both forecasting and analysing the impact of shocks or policy changes. However, the econometric estimation of systems of equations for sectoral activity requires assumptions and techniques that sufficiently reduce the parameter space.

Appendix

A1. Factors

Stock and Watson (2002a, 2002b) develop a two-step procedure that leads to the computation of forecasts for the variable of interest. First the time series of factors are estimated; then the relationship between the variable to be forecasted and the estimated factors (and possibly other observed variables) is estimated.

Let y_{t+h} be the variable to be forecasted and let $X_t = (X_{1t}, X_{2t}, \dots, X_{Nt})'$ be a vector of predictors available for $t = 1, 2, \dots, T$ then

$$X_{it} = \lambda_i(L) f_t + \eta_{it} \qquad i = 1, 2, \dots, N \tag{A1}$$

$$y_{t+h} = \beta(L) f_t + \gamma(L) W_t + \varepsilon_{t+h} \tag{A2}$$

where f_t denotes the vector of $\tilde{r}$ common *dynamic* factors, η_{it} is the idiosyncratic error associated with the i –th predictor, W_t is a $k \times 1$ vector of observed variables and the lag polynomials $\lambda_i(L)$, $\beta(L)$, $\gamma(L)$ are at most of order q with $\lambda_i(L) = \sum_{j=0}^{q} \lambda_{ij} L^j$, $\beta(L) = \sum_{j=0}^{q} \beta_j L^j$, $\gamma(L) = \sum_{j=0}^{q} \gamma_j L^j$. The idiosyncratic errors are allowed to be correlated across time periods and different predictors in the dataset, i.e. errors are serially and cross-sectionally correlated (Stock and Watson 2002a, 2002b).

Let $F_t = (f_t', f_{t-1}', \dots, f_{t-q}')'$ be an $r \times 1$ vector with $r \leq \tilde{r}(q+1)$; let Λ be the matrix of factor loadings and its i –th row is given by $(\lambda_{i0}, \lambda_{i1}, \dots, \lambda_{iq})$, then the static representation of the dynamic factor model in (A1) and (A2) is written as

$$X_t = \Lambda F_t + \eta_t \tag{A3}$$

$$y_{t+h} = \beta' F_t + \gamma(L) W_t + \varepsilon_{t+h} \tag{A4}$$

where $\beta = (\beta_0, \beta_1, \dots, \beta_q)'$ and $\eta_t = (\eta_{1t}, \eta_{2t}, \dots, \eta_{Nt})'$. Under some assumptions about the factor loadings and the moments of the idiosyncratic errors, factors can be consistently estimated using the method of principal components whereby the estimated factors $\hat{F}$ are given by the first r eigenvectors of the $T \times T$ data matrix, XX', and the estimated factor loadings are computed as $\widehat{\Lambda} = T^{-1} X' \hat{F}$, where $X = (X_1' \, X_2' \dots X_T')'$ and $\hat{F} = (\hat{F}_1' \, \hat{F}_2' \dots \hat{F}_T')'$. In order for the factors to be uniquely identified the normalisation $T^{-1} \hat{F}' \hat{F} = I_r$ is required. [20, 21]

[20] Further details about estimation and asymptotic properties of the estimators can be found in Stock and Watson (2002b).

[21] Alternatively factors and factor loadings can be computed from the $N \times N$ matrix $X'X$, but when $N > T$ it is computationally easier to follow the approach described (see Stock and Watson 2002b).

A2. Data

TABLE A1

Number of series in the dataset by category

Category	Number of series
Domestic series	188
Activity	80
Labour market	38
Price indices	5
Interest rates	13
Fiscal variables	7
Stock market indicators	4
Business and consumer surveys	23
Loans and deposits	18
Foreign/international series	143
Activity and labour market	42
Price indices	5
Commodity prices	13
Stock market indicators	22
Interest rates and spreads	31
Business and consumer surveys	24
Exchange rates	6
All series	331

FIGURE A1

GDP and its production-side components, year-on-year percentage change (%)

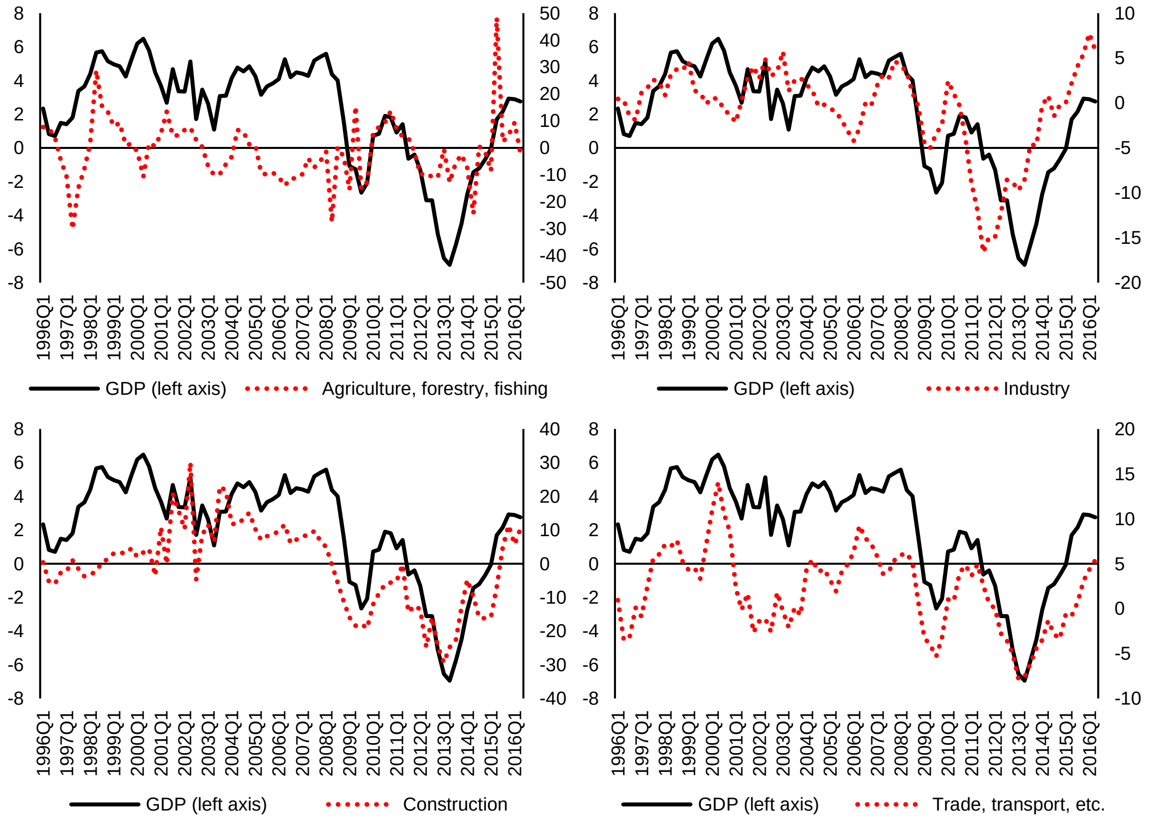
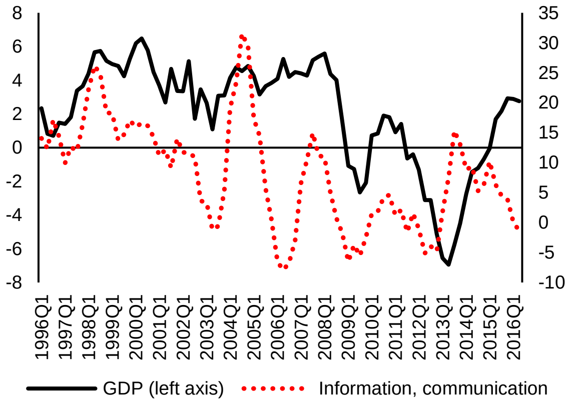
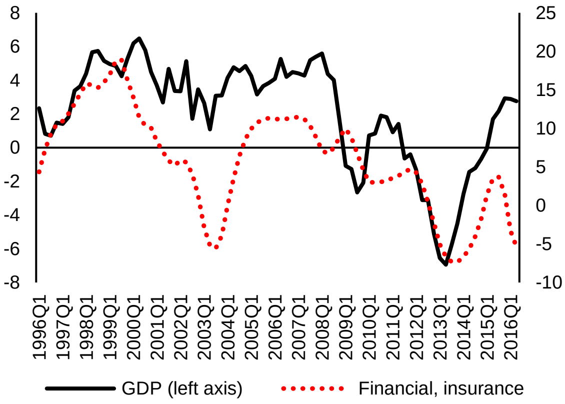
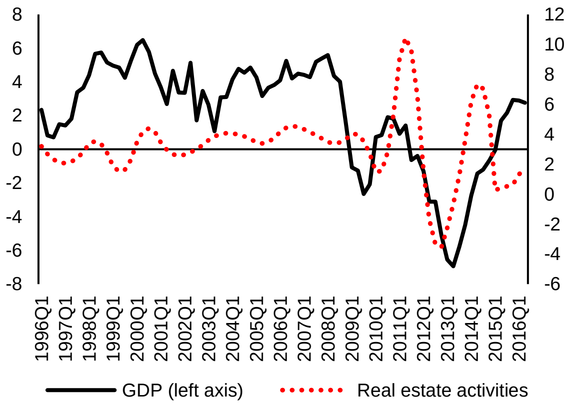
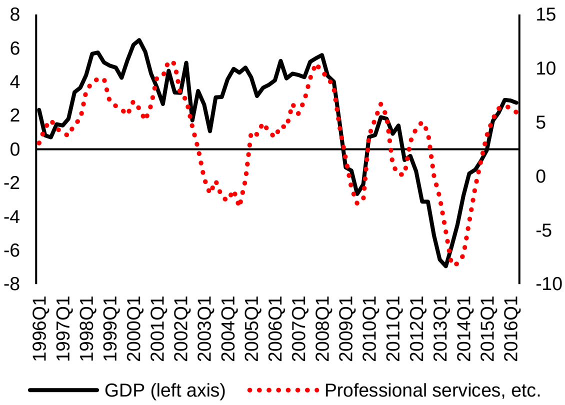


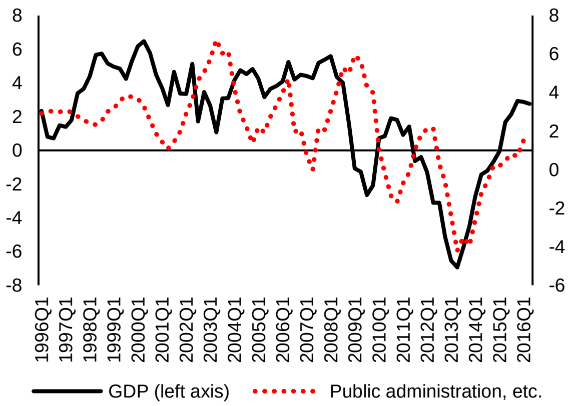
Figure A1 (continued)

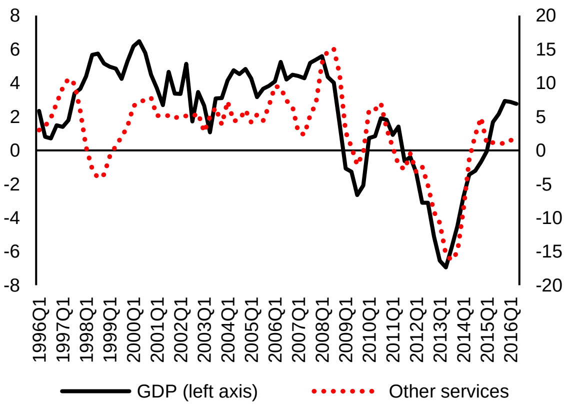


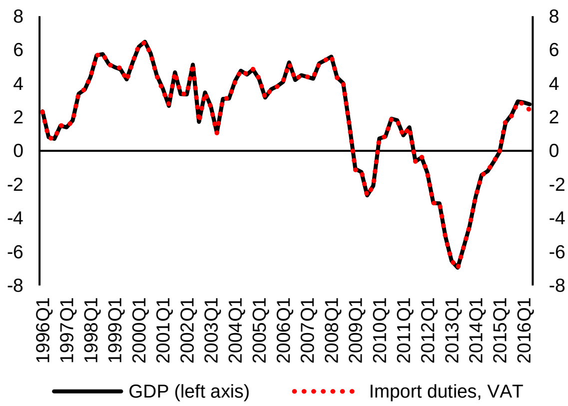












A3. Bottom-up GDP growth forecasts

Another method to compute indirect GDP forecasts is by aggregation of the component forecasts obtained from *single equation models* to get as many different forecasts for GDP as the number of models estimated i.e.

$$\hat{Z}_{t+h}^{(GDP,i)} = \sum_{s=1}^{S} \hat{Z}_{t+h}^{(s,i)}$$

where $\hat{Z}_{t+h}^{(s,i)}$ is the forecasted level of component s implied by the corresponding growth forecast for period $t+h$ from model i , incorporating information up to period t; $\hat{Z}_{t+h}^{(GDP,i)}$ is the resulting forecast for the level of GDP that is subsequently transformed into growth rate. The resulting GDP growth rates for all i are then combined using forecast combinations described in section 2 to form a single GDP growth forecast. This method is computationally more intensive than the method discussed in section 4. [22] The RMFSE of bottom-up forecasts relative to that of the direct GDP growth forecasts from the random walk model is shown in Table B1.

TABLE A2

RMSFE relative to random walk, GDP growth (bottom-up approach using component model forecasts)

Forecast horizon (quarters)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Random walk benchmark, RMSFE	1.10	2.09	3.15	4.25	4.46	4.68	4.92	5.17
Based on component univariate model forecasts								
Random walk	1.10	1.05	1.04	1.04	1.04	1.04	1.05	1.05
AR(AIC)	**0.78**	**0.81**	**0.85**	0.90	0.94	0.97	0.99	1.02
AR(BIC)	**0.84**	**0.85**	**0.88**	0.95	0.96	1.00	1.01	1.02
AR(1)	**0.92**	**0.90**	**0.89**	0.93	0.95	0.97	1.00	1.01
AR(4)	**0.77**	**0.80**	**0.81**	0.87	0.92	0.97	0.99	1.01
Based on component ADL/FAR/FADL model forecasts combined into a single GDP growth forecast								
Median	**0.79**	**0.75**	**0.80**	0.88	0.91	0.97	0.99	1.01
Mean	**0.78**	**0.74**	**0.78**	0.87	0.90	0.95	0.98	1.02
Trimmed mean (5% trimming)	**0.78**	**0.74**	**0.79**	0.88	0.91	0.96	0.99	1.02
Discounted MSFE (0.90)	**0.77**	**0.72**	**0.77**	0.86	0.88	0.95	0.98	1.02
Discounted MSFE (0.95)	**0.78**	**0.72**	**0.77**	0.86	0.89	0.95	0.98	1.02
Discounted MSFE (1.00)	**0.78**	**0.73**	**0.77**	0.86	0.89	0.95	0.98	1.02
Squared discounted MSFE (0.90)	**0.75**	**0.71**	**0.76**	0.84	0.87	0.93	0.97	1.01
Squared discounted MSFE (0.95)	**0.76**	**0.71**	**0.76**	0.85	0.88	0.95	0.98	1.02
Squared discounted MSFE (1.00)	**0.77**	**0.72**	**0.77**	0.86	0.88	0.95	0.98	1.02

Note: Entries in bold denote statistical significance at 10% level of the modified Diebold-Mariano test of equal forecast accuracy (Diebold and Mariano 1995; Harvey et al. 1997). The tests compare the forecast errors from the benchmark model (random walk) to those from the forecast combinations or univariate models shown in the table.

AR(AIC) and AR(BIC) denote the autoregressive models with lag length selected using the Akaike and Bayesian information criteria, respectively; AR(1) and AR(4) are the autoregressive models of order one and four, respectively.

For the discounted and squared discounted MSFE forecast combination methods the discount factor is given in parentheses.

[22] When pre-selected predictors are used for modelling and component growth, the number of forecasting models differ for each component and therefore aggregation is more complex.

TABLE A3

RMSFE relative to squared discounted MSFE (0.90) combination from the direct approach, GDP growth (bottom-up approach using component model forecasts)

Forecast horizon (quarters)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Benchmark: Squared discounted MSFE (0.90), RMSFE	0.80	1.36	2.21	3.08	3.52	4.05	4.44	4.92
Based on component univariate model forecasts								
Random walk	**1.52**	**1.61**	**1.48**	**1.44**	**1.32**	1.21	1.16	**1.10**
AR(AIC)	1.08	**1.25**	**1.20**	**1.25**	1.19	1.13	1.10	**1.07**
AR(BIC)	**1.16**	**1.31**	**1.25**	**1.31**	1.22	1.15	1.12	1.07
AR(1)	**1.27**	**1.38**	**1.26**	**1.29**	1.20	1.13	1.11	**1.06**
AR(4)	1.06	**1.23**	1.16	1.21	1.16	1.12	**1.10**	**1.07**
Based on component ADL/FAR/FADL model forecasts combined into a single GDP growth forecast								
Median	1.09	**1.16**	1.13	**1.22**	**1.15**	1.12	1.09	**1.06**
Mean	1.08	**1.13**	1.11	**1.21**	1.14	1.10	**1.09**	**1.07**
Trimmed mean (5% trimming)	1.08	**1.14**	1.12	**1.22**	1.15	1.11	**1.09**	**1.07**
Discounted MSFE (0.90)	1.06	1.11	1.09	**1.19**	**1.12**	1.10	**1.08**	**1.07**
Discounted MSFE (0.95)	1.07	1.11	1.10	**1.19**	1.13	1.10	**1.09**	**1.07**
Discounted MSFE (1.00)	1.08	1.12	1.10	**1.20**	1.13	1.10	**1.09**	**1.07**
Squared discounted MSFE (0.90)	1.04	1.09	1.07	**1.17**	**1.10**	**1.08**	**1.07**	**1.07**
Squared discounted MSFE (0.95)	1.06	1.09	1.08	**1.18**	**1.11**	**1.09**	**1.08**	**1.07**
Squared discounted MSFE (1.00)	1.07	1.10	1.09	**1.19**	**1.12**	**1.10**	**1.09**	**1.07**

Note: Entries in bold denote statistical significance at 10% level of the modified Diebold-Mariano test of equal forecast accuracy (Diebold and Mariano 1995; Harvey et al. 1997). The tests compare the forecasts errors from the benchmark model (squared discounted MSFE with a discount factor equal to 0.90) to those from the methods listed in the table.

AR(AIC) and AR(BIC) denote the autoregressive models with lag length selected using the Akaike and Bayesian information criteria, respectively; AR(1) and AR(4) are the autoregressive models of order one and four, respectively.

For discounted and squared discounted MSFE forecast combination methods the discount factor is given in parentheses.

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