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Can Measures of Broadband Infrastructure Improve Predictions of Economic Growth?

October 29, 2014

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Abstract

This paper investigates whether predictions of future economic growth can be improved by using standard measures of broadband infrastructure. The investigation is carried out by comparing the predictive accuracy of dynamic panel models of economic growth estimated with and without measures of broadband infrastructure. Tests of predictive accuracy are employed to test the hypothesis that measures of broadband infrastructure can improve predictions of GDP growth after controlling for standard growth determinants.

Keywords: Broadband speed; economic growth; hypothesis tests; prediction;

1. Introduction

The development of broadband infrastructure is regarded as important by policymakers in many countries. A key motive is the belief that increased broadband deployment will stimulate economic growth. Empirical support for the notion that broadband infrastructure is an important source of economic growth has been provided by Koutroumpis (2009), Czernich et al. (2011) and Madden, Mayer and Wu (2014). In view of this evidence, the present paper investigates whether standard measures of broadband infrastructure are useful for out of sample predictions of future economic growth. The investigation is carried out by comparing the predictive accuracy of dynamic panel models of GDP with and without measures of broadband infrastructure. The data are for 29 OECD countries for the period 2008 to 2012. Following previous

studies, the latter measures are broadband penetration, speed and the number of years since broadband was introduced. Various goodness-of-fit statistics are available for making such comparisons but cannot determine if differences in predictive accuracy are purely sampling errors. To control for sampling error requires formal hypothesis tests. Formal hypothesis tests of predictive accuracy have been proposed and developed by Granger and Newbold (1977), Diebold and Mariano (1995), West (1996), Harvey, Leybourne and Newbold (1997) and others. Two that have become standard are the Morgan-Granger-Newbold (MGN) and Diebold-Mariano (DM) tests. Recently, Dang, Mayer and Xu (2014) propose modifications of the DM and MGN tests that improve asymptotic power by exploiting available sample information more fully to estimate the tested parameters. These tests are employed to test the hypothesis that measures of broadband infrastructure can improve predictions of GDP growth after controlling for standard growth determinants.

2. Prediction Model

Following Madden, Mayer and Wu (2014), we specify a dynamic panel model with fixed effects.¹ The model has the form:

$$y_{it} = \sum_{j=1}^2 \delta_j y_{i,t-j} + x_{it} \beta + z_{it} \gamma + u_i + \varepsilon_{it} \quad (1)$$

where y_{it} denotes the logarithm of national GDP per capita for country i ($=1, \dots, n$) at time t ($=1, \dots, T$), x_{it} is a vector of growth determinants and z_{it} a vector of measures of broadband infrastructure. The lagged values $y_{i,t-j}$ can be motivated by adjustment lags that allow changes in the explanatory variables and errors to impact GDP in future periods. The variables in x_{it} include the ratio of capital formation to GDP (*CAPGDP*), an education index (*EDU*), the growth rate of the labor force (*LABOR*) and a share price index (*SHAREPRICE*). The latter variable controls

¹ Equation (1) is a simplified version of the model estimated by Madden, Mayer and Wu (2014). The model estimated in that study allows the coefficients to vary by income group. This additional source of endogeneity raises new issues for the present prediction problem which have yet to be addressed in the literature. The purpose of the present paper is to assess the predictive content of broadband infrastructure using a standard dynamic panel data model. Hence, (1) suffices for the present paper.

for the Global Financial Crisis which occurred during our sample period (2008-2012), while the former variables are standard determinants of steady-state growth. Also included in x_{it} is a time trend ($TREND$) and interactions with regional dummy variables ($TREND \times REGION_j$), which capture region-specific growth for selected regions. Three measures of broadband infrastructure in z_{it} are broadband penetration (PEN), broadband speed ($SPEED$) and the number of years since broadband was introduced ($YEAR$). All measures are expected to be positively related to economic growth. To allow for the possibility that the impact of increased broadband speed on economic growth depends on the existing level of penetration, and the interaction term, $PEN \times SPEED$ is also included in z_{it} . The fixed effect α_i reflects time-invariant country-specific factors such as initial conditions that influence growth and may be correlated with the observed explanatory variables. The error term ε_{it} captures shocks that vary over both i and t . Table 1 provides definitions, means and standard deviations for the variables. We report and discuss the Arellano-Bond GMM estimates of (1) in section 4 below.

Table 1. Variable Definitions and Descriptive Statistics

| Variable | Definition | Mean | SD |
|-------------------------------------|--|----------|----------|
| Dependent variable | | | |
| GDPPC | = Real GDP per capita (quarterly) | 9009.689 | 3350.091 |
| Economic and demographic conditions | | | |
| LABOR | = Change in growth of working-age (15+) population | -.000214 | .0250718 |
| EDU | = Years of schooling | 10.8707 | 1.502812 |
| CAPGDP | = Gross fixed capital formation / GDP (quarterly) | .2028873 | .035515 |
| SHAREPRICE | = All-share price indices (quarterly) (2005 = 100) | 102.4766 | 52.63776 |
| Broadband developments | | | |
| PEN | = Fixed broadband subscribers per 100 inhabitants | 26.21154 | 8.180294 |
| SPEED | = Real broadband download speed | 11316.35 | 6739.085 |
| YEAR | = Years since broadband are introduced | 10.24138 | 1.907266 |

Notes: for estimation, log is used for GDPPC, EDU, CAPGDP, and SHAREPRICE.

To investigate whether standard measures of broadband infrastructure are useful for predicting future economic growth, predictions were generated from two models. The first (Model 1) includes all of the broadband variables: PEN, SPEED, PEN*SPEED and YEAR. The second (Model 2) excludes all of the broadband variables. For each model, predictions of $y_{i,t+h}$ for $h=1,2$ were computed conditional on the assumed information set. For Model 1, the information set is: $\Omega_{i,t+h|t} = \{ (y_{i,r}, x_{i,s}, z_{i,s}) : r=1, \dots, t; s=1, \dots, t+h \}$. For Model 2 the information set excludes z_{it} but is otherwise the same. Let $X_{it}\Gamma = x_{it}\beta + z_{it}\gamma$, $V_{it} = u_i + \varepsilon_{it}$, and $\hat{\delta}_1, \hat{\delta}_2, \hat{\Gamma}$ denote estimates. The predictors have the form:

$$\hat{y}_{i,t+1|t} = \hat{\delta}_1 y_{i,t} + \hat{\delta}_2 y_{i,t-1} + X_{i,t+1} \hat{\Gamma} + \hat{V}_{i,t+1|t} \quad (2)$$

$$\hat{y}_{i,t+2|t} = \hat{\delta}_1 \hat{y}_{i,t+1|t} + \hat{\delta}_2 y_{i,t} + X_{i,t+2} \hat{\Gamma} + \hat{V}_{i,t+2|t} \quad (3)$$

The predicted values of the first three terms on the RHS of the above equations are straightforward. To predict $V_{i,t+h}$, we use a linear projection of $V_{i,t}$. The linear projection of $V_{i,t+h}$ on $\Omega_{i,t+h|t}$ is

$$E^*(V_{i,t} | \Omega_{i,t+h|t}) = \pi_0 + \sum_{s=1}^{t+h} \pi_{1ts} x_{is} + \sum_{s=1}^{t+h} \pi_{2ts} Y_{is} + \sum_{s=1}^t \pi_{3ts} y_{is} \quad (4)$$

Consistent estimates of the coefficients can be obtained by applying OLS to:

$$y_{it} - \hat{\delta}_1 y_{i,t-1} - \hat{\delta}_2 y_{i,t-2} - x_{it} \hat{\beta} - Y_{it} \hat{\gamma} = \pi_0 + \sum_{s=1}^{t+h} \pi_{1ts} x_{is} + \sum_{s=1}^{t+h} \pi_{2ts} Y_{is} + \sum_{s=1}^t \pi_{3ts} y_{is} + \eta_{it} \quad (5)$$

for $i=1, \dots, n$; $t=1, \dots, T$, where η_{it} denotes the projection error. The coefficients generally depend on t as functions of the covariances: $\text{cov}(x_{is}, u_i + \varepsilon_{it})$, $\text{cov}(Y_{is}, u_i + \varepsilon_{it})$ and $\text{cov}(y_{is}, u_i + \varepsilon_{it})$. The problem this poses is that a large number of coefficients must be estimated. If we assume that the covariances do not depend on i , x_{is} is uncorrelated ε_{it} and that the vector $(Y_{it}, \varepsilon_{it})$ is

covariance-stationary, then $\pi_{1st} = \pi_{1s}$, $\pi_{2st} = \pi_{2s,t-s}$ and $\pi_{3st} = \pi_{3s,t-s}$.² However, in our application $n=29$ and $T=16$. Consequently, even under these restrictions the number of coefficients generally exceeds the number of observations available to estimate (4). To resolve the problem, instead of $E^*(V_{it} | \Omega_{it})$ we use the linear projection $E^*(V_{it} | \bar{x}_i)$ where $\bar{x}_i = (t+h)^{-1} \sum_{t=1}^{t+h} x_{it}$. By iterated projections, $E^*(V_{it} | \bar{x}_i) = E^*[E^*(V_{it} | \Omega_{it}) | \bar{x}_i]$ and, consequently, the linear projection $E^*(V_{it} | \bar{x}_i)$ can be viewed as a best linear predictor of $E^*(V_{it} | \Omega_{it})$.

3. Hypothesis Tests of Predictive Accuracy

Given a sample of P predictions for country i , let $\hat{y}_{ip(j)}$ and $e_{ip(j)}$ denote, respectively, the p th ($p=1, \dots, P$) prediction and prediction error from the Model $j=1,2$. For the two models, we will test the null hypothesis of equal predictive accuracy:

$$H_o : \theta = 0 \quad \text{versus} \quad H_1 : \theta < 0 \quad (6)$$

where $\theta = E(e_{ip(1)}^2 - e_{ip(2)}^2)$. The alternative is one-sided. If the null is rejected, we are able to conclude that Model 1 with broadband variables yields a more accurate prediction on GDP growth than Model 2 does.

Let $d_{ip} = e_{ip(1)}^2 - e_{ip(2)}^2$. The original Diebold-Mariano 1995 (DM) test is designed for time-series and is based on the sample mean of the difference between the squared prediction errors. An analogous test for panel data is:

$$DM_e = \hat{\theta}_e \sqrt{N / \hat{V}_e}, \quad (7)$$

where

² Under these assumptions, $\text{cov}(x_{is}, u_i + \varepsilon_{it})$ depends only on s , while $\text{cov}(Y_{is}, u_i + \varepsilon_{it})$ and $\text{cov}(y_{is}, u_i + \varepsilon_{it})$ depend only on s and $t-s$.

$$\hat{\theta}_e = \frac{1}{NP} \sum_{i=1}^N \sum_{p=1}^P d_{ip} = \frac{1}{N} \sum_{i=1}^N \frac{1}{P} \sum_{p=1}^P d_{ip} = \frac{1}{N} \sum_{i=1}^N \bar{d}_i = \bar{d}_{..}$$

and

$$\hat{V}_e = \frac{1}{N-1} \sum_{i=1}^N (\bar{d}_i - \bar{d}_{..})^2.$$

The covariance estimator, \hat{V}_e , assumes that the prediction errors are uncorrelated across countries but allows serial correlation. Under this assumption and the null hypothesis (6), (7) converges to the standard normal distribution as N approaches infinity for fixed P. The null hypothesis also implies that the mean of \bar{d}_i is zero. Following Dang, Mayer and Xu (2014), we also consider a version of (7) with this restriction imposed on \hat{V}_e and denote it by DMV_e .

Like the original DM test, the Morgan-Granger-Newbold (MGN) test is designed for time-series but is based on the sample correlation between the difference and sum of the prediction errors. Unlike the DM test, the MGN test assumes normally distributed prediction errors. An MGN-type test for panel data can be devised in terms of the country means:

$$\bar{e}_{i(j)} = \frac{1}{P} \sum_{p=1}^P e_{ip(j)} \quad \text{for } j=1, 2 \quad (8)$$

The MGN test for panel data is

$$MGN_e = \hat{\rho}_e \sqrt{(N-1) / (1 - \hat{\rho}_e^2)} \quad (9)$$

where $\hat{\rho}_e$ is the sample correlation between $\bar{e}_{i(1)} + \bar{e}_{i(2)}$ and $\bar{e}_{i(1)} - \bar{e}_{i(2)}$. Under (6) and normally distributed prediction errors that are uncorrelated across countries, (9) also converges to the standard normal distribution.

The above DM and MGN tests depend on the predictions $\hat{y}_{ip(j)}$ only through the prediction errors $e_{ip(j)}$. Dang, Mayer and Xu (2014) propose alternative versions of the DM and MGN tests based directly on the predictions. The panel data analog of the DM test is based on the following alternative estimator of θ :

$$\hat{\theta}_y = \frac{1}{NP} \sum_{i=1}^N \sum_{p=1}^P (\hat{y}_{ip(1)} - \hat{y}_{ip(2)}) (\hat{\alpha}_1^* \hat{y}_{ip(1)} + \hat{\alpha}_2^* \hat{y}_{ip(2)}) = \frac{1}{NP} \sum_{i=1}^N \sum_{p=1}^P g_{ip} \quad (10)$$

where $\hat{\alpha}_j^* = 2\hat{\alpha}_j - 1$, $j=1,2$, and $\hat{\alpha}_j$ are estimated coefficients of the linear projection:

$$E^*(y_{it} | \hat{y}_{ip(1)}, \hat{y}_{ip(2)}) = \alpha_0 + \alpha_1 \hat{y}_{ip(1)} + \alpha_2 \hat{y}_{ip(2)}$$

Dang, Mayer and Xu (2014) assume that the number of observations used to compute the $\hat{\alpha}_j$, M , is such that $P/M \rightarrow \infty$ so that they are asymptotically irrelevant in the distribution of $\hat{\theta}_y$. To satisfy this assumption for the application in the next section, the prediction (29 times 4 observations) and estimation (29 times 16 observations) samples are combined to compute the $\hat{\alpha}_j$. Using a GMM framework, Dang, Mayer and Xu (2014) show that $\hat{\theta}_y$ is more efficient than $\hat{\theta}_e$ because it exploits available sample information more fully, and argue that tests based on $\hat{\theta}_y$ have greater power. The simulations in Dang, Mayer and Xu (2014) confirm the power gains. The panel-data analogue of the DM test proposed by Dang, Mayer and Xu (2014) is

$$DM_y = \hat{\theta}_y \sqrt{N / \hat{V}_y} \quad (11)$$

where $\hat{V}_y = \frac{1}{N-1} \sum_{i=1}^N (\bar{g}_i - \bar{g}_{..})^2$, $\bar{g}_i = \frac{1}{P} \sum_{p=1}^P g_{ip}$, and $\bar{g}_{..} = \frac{1}{N} \sum_{i=1}^N \bar{g}_i$.

The panel-data analogue of the MGN test proposed by Dang, Mayer and Xu (2014) is given by

$$MGN_y = \hat{\rho}_y \sqrt{(N-1) / (1 - \hat{\rho}_y^2)} \quad (12)$$

where $\hat{\rho}_y$ denotes the sample correlation between $\bar{\hat{y}}_{i(2)} - \bar{\hat{y}}_{i(1)}$ and $\hat{\alpha}_1^* \bar{\hat{y}}_{i(1)} + \hat{\alpha}_2^* \bar{\hat{y}}_{i(2)}$.

In addition, Dang, Mayer and Xu (2014) also propose generalized versions of the MGN test that simultaneously addresses the problems of serially correlated and heavy-tailed prediction errors. The proposed tests include as special cases the DM and MGN tests, and the modified MGN test proposed by Harvey et al. (1997). These generalized tests can also be adapted to panel data and have the form:

$$MGNV_a = DM_a (1 - \hat{\rho}_a^2)^{-1/2} N^{-1/2} (1 - N)^{1/2} \quad a = e, \bar{y} \quad (13)$$

4. Results

For the two models, one and two-step-ahead prediction errors were generated. Recall that Model 1 includes all broadband variables, but Model 2 excludes all broadband variables. The sample consists of quarterly data from the first quarter of 2008 to the fourth quarter of 2012. The four quarters of 2012 were used to compare the predictive accuracy of the three models. The Arellano-Bond estimates for (2) were computed using a recursive scheme to generate successive observations. Table 2 reports the estimates for the full sample period of 2008-2012.

Table 2: Arellano-Bond GMM estimates of Log GDP per capita growth, 2008-2012

| Number | Variable | Model 1 | | Model 2 | |
|--------|---------------------|-------------------------------|------|----------------|------|
| 1 | Log(GDPPC(-1)) | 0.7444(17.80) | **** | 0.6344(13.82) | **** |
| 2 | Log(GDPPC(-2)) | -0.0226(-0.58) | | 0.0177(0.47) | |
| 3 | PEN | 0.0009(1.31) | | | |
| 4 | SPEED | $2.2 \cdot 10^{-6}$ (2.72) | *** | | |
| 5 | PEN*SPEED | $-7.12 \cdot 10^{-8}$ (-3.17) | *** | | |
| 6 | YEAR | -0.002 (-1.34) | | | |
| 7 | Log(CAPGDP) | 0.0195 (2.19) | ** | 0.0111 (1.00) | |
| 8 | EDU | -0.0141 (0.13) | | 0.2411 (1.73) | * |
| 9 | LABOR | 0.056 (0.23) | | -0.0187 (0.81) | |
| 10 | Log(SHAREPRICE) | 0.0383 (10.47) | **** | 0.0434 (5.42) | **** |
| 11 | TREND | 0.0018 (2.97) | *** | 0.0011 (5.42) | **** |
| 12 | NORTH AMERICA TREND | -0.0004 (1.23) | | -0.0001 (0.36) | |
| 13 | PACIFIC TREND | 0.0002 (0.73) | | 0.0005 (1.08) | |

Notes: The numbers in parentheses are Z statistic values. **** significant to 0.1%; *** significant to 1%; ** significant to 5%; * significant to 10%.

The estimated coefficients for capital formation (CAPGDP), the price share index (SHAREPRICE) and time trend (TREND) have the expected positive signs in two models. However, the CAPGDP coefficient is significant only in Model I, while price-share index and trend coefficients are significant in both. The EDU coefficient is insignificant in Model I but is significant at 5% level in Model II. The estimated LABOR coefficients are insignificant in both models. The pattern of statistically significant CAPGDP coefficient and insignificant EDU and LABOR coefficients accords with the findings of Czernich et al. (2011). SPEED and the PEN *

SPEED interaction coefficients are significant, while the separate variable coefficients for PEN and YEAR are insignificant. As discussed in Madden, Mayer and Wu (2014), the statistical significance of the positive coefficient sign for broadband speed and the negative sign for interaction term imply that increased speed has more impact in countries with less broadband penetration.

| | | One-step Prediction | | Two-step Prediction | |
|---------|-----|---------------------|---------|---------------------|---------|
| | | Model 1 | Model 2 | Model 1 | Model 2 |
| With | AIC | 14.481 | 14.512 | 15.236 | 15.218 |
| | BIC | 14.790 | 14.726 | 15.544 | 15.432 |
| Without | AIC | 12.831 | 13.237 | 13.717 | 14.060 |
| | BIC | 13.147 | 13.455 | 14.032 | 14.279 |

Table 3: AIC and BIC of both models with and without Luxembourg

After the estimates were obtained, the models were applied to predict the GDPPC of the four quarters of 2012. Predictors and prediction errors of the two models were then calculated. Before applying the hypothesis tests described in the last section to compare prediction accuracy, we first consider the relative performance of the models in terms of fit. The AIC and BIC criteria were calculated for the prediction errors of each model. The results with and without Luxembourg are reported in Table 3 for a reason explained below. For both cases, the differences in the values of the AIC and BIC across models are fairly small. When all 29 countries are included in the calculations, the AIC favors Model 1 for one step ahead predictions and favors Model 2 for two step ahead predictions, while BIC favors Model 2 for both one and two-step ahead predictions.

To investigate this further, the distributions of the prediction errors for the two models were plotted. The plots are shown in Figure 1 and reveal outliers in the right tail. The outliers in the right tail correspond to Luxembourg which has the largest GDP per capita in the sample. Apart from the outlier, the distributions of the prediction errors appear to be approximately normal centered at zero. The plots suggest that Model 1 has a smaller variance than Model 2, and, therefore, support the notion that the broadband variables are important predictors of economic growth. Recalculating the AIC and BIC after deleting Luxembourg, we now find that Model 2 is now ranked inferior to the Model 1 in all cases. With and without Luxembourg, different

conclusions of AIC and BIC can be explained by the fact that AIC and BIC are normal log-likelihood based and hence are sensitive to outliers.

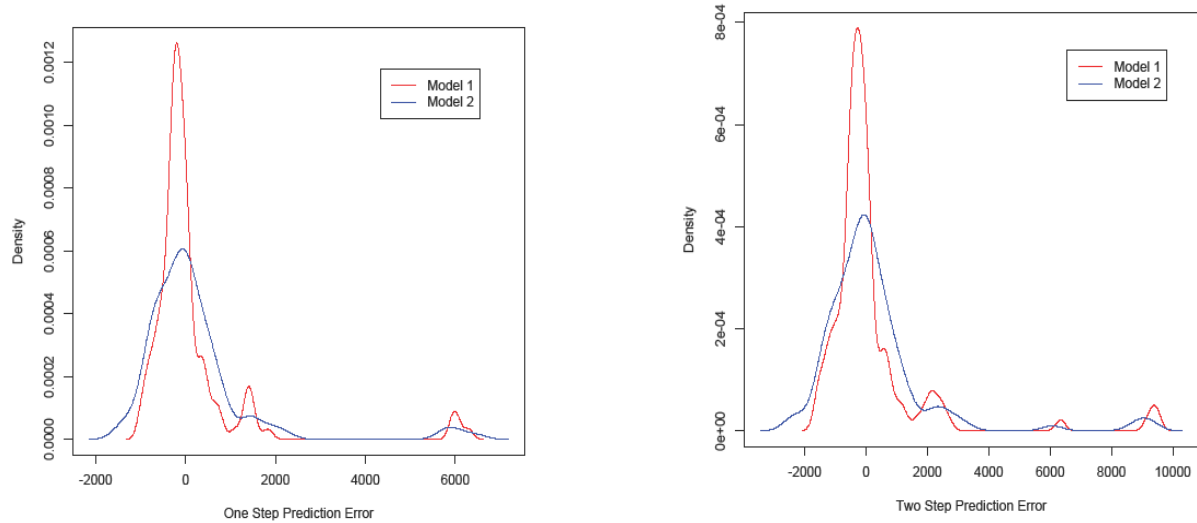


Figure 1: Density estimation of one and two-step ahead prediction errors for the models.

To determine if the differences in predictive accuracy are statistically significant, we next apply the tests described in Section 3. The eight tests (4 based on prediction errors, 4 based on predictors) were computed for the one-step and two-step predictions. The tests were carried out with and without Luxembourg. Table 3 reports the p-values of the tests. The tests clearly favor Model 1 over Model 2 as only 2 of the 16 tests are not significant at conventional levels significance with Luxembourg included. Without Luxembourg, all tests unambiguously claim that Model 1 has greater predictive accuracy than Model 2, and therefore measures of broadband infrastructure can improve predictions of economic growth.

We also note that the tests based on the predictors are generally more significant than the tests based on the prediction errors. This is not surprising given that the tests based on the predictors are asymptotically more powerful because they exploit available sample information more fully and are better able to detect small predictive differences between two models. MGNV tests are most significant among 4 tests on all cases. Such findings agree with the simulation results in Dang, Mayer and Xu (2014).

| | | DM | | DMV | | MGN | | MGNV | |
|---------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| | | <i>e</i> | <i>y</i> | <i>e</i> | <i>y</i> | <i>e</i> | <i>y</i> | <i>e</i> | <i>y</i> |
| With | One-step | .0096 | .0023 | .0159 | .0060 | .1440 | .0032 | .0000 | .0000 |
| | Two-step | .0912 | .0000 | .0978 | .0005 | .5082 | .0000 | .0038 | .0000 |
| Without | One-step | .0047 | .0017 | .0099 | .0053 | .0032 | .0005 | .0000 | .0000 |
| | Two-step | .0000 | .0000 | .0002 | .0000 | .0011 | .0005 | .0000 | .0000 |

Table 4: P-values of various tests for model forecasting accuracy with and without Luxembourg included.

With Luxembourg included, the MGN test based on prediction errors is the only test insignificant for one-step and two-step predictions. It becomes significant when the outlier Luxembourg is deleted. This can be explained by the normally distributed assumption of the MGN test, which is obviously not satisfied if Luxembourg is included. As expected, tests on the predictors are more significant in two-step than in one-step ahead predictions. Recall that two-step ahead predictor depends on one-step ahead predictor in equation (3). If a test is significant in one-step ahead predictions, then we would expect to be also significant in two-step ahead predictions. Such results only hold for tests on based on the prediction errors with Luxembourg excluded. Tests based on the prediction errors for two-step ahead predictions, however are less significant than that for one-step ahead predictions with outliers included. In this sense, tests on the predictors are more robust than tests on the prediction errors.

5. Concluding Remarks

This paper investigated whether predictions of future economic growth can be improved by using standard measures of broadband infrastructure. The measures of broadband considered in the paper are penetration, speed and the number of years since broadband was introduced. The investigation was carried out by comparing the predictive accuracy of dynamic panel models of economic growth estimated with and without those measures of broadband infrastructure using the data of 29 OECD countries for the period 2008 to 2012. One-step and two-step ahead predictions were considered and compared for the two models. Adapted from tests for time-series data, we devised eight tests for panel data and performed them to compare predictive accuracy. Although the outliers contained in the data set complicate the problem, the tests

clearly favor the model with broadband variables. Among those eight tests, tests based on the predictors are more powerful and more robust than those based on the prediction errors. Also, the generalized MGNV tests are recommended.

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