Tasmanian School of Business and Economics
University of Tasmania

Discussion Paper Series N 2016-04

Forecasting Output Gaps in the G-7 Countries: The Role of Correlated Innovations and Structural Breaks.

Mardi Dungey
University of Tasmania, CFAP and CAMA
Australia

Jan P.A.M. Jacobs
University of Groningen, Netherlands
University of Tasmania, CAMA and CIRANO
Australia

Jing Tian
University of Tasmania
Australia

ISBN 978-1-86295-889-0

Forecasting output gaps in the G-7 countries: the role of correlated innovations and structural breaks

Mardi Dungey*
University of Tasmania, CFAP and CAMA

Jan P.A.M. Jacobs
University of Groningen, University of Tasmania, CAMA and CIRANO

Jing Tian
University of Tasmania

This version: December 2016

Abstract

Trend GDP and output gaps play an important role in fiscal and monetary policy formulation, often including the need for forecasts. In this paper we focus on forecasting trend GDP and output gaps with Beveridge-Nelson (1981) trend-cycle decompositions and investigate how these are affected by assumptions concerning correlated innovations and structural breaks. We evaluate expanding windows, one-step-ahead forecasts indirectly for the G-7 countries on the basis of real GDP growth rate forecasts. We find that correlated innovations affect real GDP growth rate forecasts positively, while allowing for structural breaks works for some countries but not for all. In the face of uncertainty the evidence supports that in making forecasts of trends and output gap policy makers should focus on allowing for the correlation of shocks as an order of priority higher than unknown structural breaks.

JEL classification: C22, C53, C82
Keywords: trend, output gap, trend-cycle decomposition, real GDP, forecasts, structural break
Number of words: 2835

*Corresponding author: Mardi Dungey, Tasmanian School of Business and Economics, Private Bag 84, University of Tasmania, Tasmania, 7001, Australia. Phone: +61-3-62261839. Email: Mardi.Dungey@utas.edu.au

1 Introduction

Forecasts of output gaps play an important role in fiscal and monetary policy formulation. A comprehensive review by Wieland and Wolters (2013) of forecasting for macroeconomic policy makers demonstrates both the practical importance of such forecasts—feeding into decision making and fiscal planning for example—and the inherent risks due to model uncertainty, model choices and the path dependency of the forecasts on the policy decisions taken. Output gap forecasts, for example, are critical inputs to policy maker discussions such as the future level of debt and sustainability of the budget deficit as well as the Taylor rule.

This paper examines the relative importance of accounting for the impact of correlated trend and cycle innovations and structural breaks on *forecasting* trend output and output gaps. While a range of methods exist to estimate trend output and output gaps with historical data, see Kiley (2013), we focus on the unobserved components model of Beveridge-Nelson (1981) trend-cycle decomposition. We apply the univariate unobserved component model to forecast one-step ahead trends and output gaps for the G-7 countries.

The implications of correlated innovations and structural breaks in forecasting trends and output gaps have not been studied extensively before. The existing literature focuses on the *measurement* of real GDP trend and output gaps and emphasises the impact of correlation between trend and cycle innovations and structural breaks. It suggests that controlling for trend breaks is more important in the *measurement* of output than allowing for the potential correlation of trend and cycle innovations. Perron and Wada (2009) demonstrate this particularly with the strong finding that the trend is deterministic and innovations to the trend and cycle effectively become uncorrelated after breaks are accommodated; see also the updated sample period in Luo and Startz (2014) who find a weak correlation between trend and cycle shocks.

We adopt a *forecast* user's perspective and evaluate forecasts of unobserved components indirectly on the basis of real GDP growth rate forecasts. We observe that for many of the G-7 countries allowing for correlations between the innovations plays a similar role as allowing for breaks in the drift of trend, that is to produce deeper declines in trend forecasts during periods of stress than otherwise.

Importantly, we find that correlated innovations improve real GDP growth rate forecasts across the G-7 countries, while allowing for structural breaks works for some countries but not for all. We conclude that in the face of unknown structural breaks it is more advisable for the forecasting policy maker to ensure they control for the historically detectable correlation between innovations in cycle and trend, than to be concerned about accommodating breaks.

The remainder of the paper is structured as follows. Section 2 discusses trend-cycle decomposition, accounting for correlated innovations, detecting structural breaks and forecast evaluation. Section 3 describes our data and the evidence for structural breaks. Section 4 presents forecasts of real GDP, trends and output gaps, accounting for various combinations of correlated and uncorrelated innovations and no structural break and structural break specifications. Section 5 gives forecast evaluation outcomes. Section 6 concludes.

2 Methodology

2.1 Trend-cycle decomposition

We decompose seasonally-adjusted real GDP in natural logarithm (y_t) into a trend (τ_t) and an output gap or cycle (c_t), that is

$$y_t = \tau_t + c_t, \tag{1}$$

and the dynamics of the components τ_t and c_t are modeled as

$$\begin{aligned} \tau_t &= \mu + \tau_{t-1} + u_{\tau,t} \\ \phi_p(L)c_t &= u_{c,t}. \end{aligned} \tag{2}$$

In the above model the roots of the $AR(p)$ polynomial $\phi_p(L) = 1 - \rho_1 L - \rho_2 L^2 - ... - \rho_p L^p$ are greater than one. The innovation vector $\mathbf{v}_t = (u_{\tau,t}\ u_{c,t})'$ is i.i.d normally distributed with $\mathbf{E}(\mathbf{v}_t) = \mathbf{0}$ and covariance matrix

$$\mathbf{Q} \equiv \begin{bmatrix} \sigma_\tau^2 & \sigma_{\tau,c} \\ \sigma_{\tau,c} & \sigma_c^2 \end{bmatrix}. \tag{3}$$

If we assume orthogonal innovations as in the seminal model of Watson (1986), then $\sigma_{\tau,c} = 0$. Alternatively, we can assume non-zero correlations between trend and output gap innovations, as in Morley, Nelson and Zivot (2003; henceforth MNZ).

This unobserved component model for real GDP y_t has an associated ARIMA(p,1,q) reduced form given by

$$\phi_p(L)\Delta y_t = \mu\phi_p(L) + \phi_p(L)u_{\tau,t} + \theta_q(L)\Delta u_{c,t}, \tag{4}$$

where $q = \max(p, 1)$. For example, an ARIMA(2,1,2) reduced form associated to $p = 2$ implies three non-zero autocovariances for exactly identifying σ_τ, σ_c and $\sigma_{\tau,c}$ in Equation (3). When $p = 1$, the associated reduced form is ARIMA(1,1,1) and the covariance matrix of (3) is under-identified. When $p > 2$, this covariance matrix is over-identified. These identification conditions suggest that the estimation of the covariance matrix of innovations in the transition equations requires $p \geq 2$, see also MNZ, Proietti (2006), Dungey et al. (2015) and Iwata and Li (2015).

In our empirical analyses we adopt an AR(2) process for the cycle process as in

Clark (1987) and MNZ. This lag structure is widely used empirically and it is the most parsimonious structure that satisfies the identification requirement.

In Equation (2) the trend of real GDP follows a process of a random walk with a drift μ. Perron and Wada (2009) modify this equation by allowing the deterministic part, μ, to change permanently after a structural break. We follow them, but allow multiple structural breaks in the trend function, such that

$$\tau_t = \mu_{T_{j-1}+1:T_j} + \tau_{t-1} + u_{\tau,t}, \; j = 1, 2, ..., m+1 \text{ and } T_{j-1} + 1 \leq t \leq T_j, \tag{5}$$

where m denotes the total number of breaks, and $T_0 = 0$ and $T_{m+1} = T$.

Detecting unknown structural breaks in the UC framework is not trivial.[1] However, we can detect and date the breaks in the reduced form of Equation (4): a drift break in trend function is equivalent to a mean shift of the GDP growth series. Therefore we apply the Bai-Perron algorithm for detecting and dating break dates (Bai and Perron, 1998, 2003) to the mean of the growth rate of real GDP. Several studies have taken this simple route to detect structural breaks in the drift of the unobserved trend, see for example, Basistha and Nelson (2007) and Mitra and Sinclair (2012).

If a drift break is identified in the past sample up to time t, we modify the trend process. Taking the conventional view that the observations after the last break point D_t are the most relevant to forecasting the future[2], we incorporate only the last estimated break point $\widehat{T}_{lb}$ for the purpose of forecasting, that is

$$\tau_t = \mu + \beta \times D_t + \tau_{t-1} + \nu_{\tau,t}, \text{ where } D_t = 1 \text{ for } t \geq \widehat{T}_{lb} \text{ and } D_t = 0 \text{ for } t < \widehat{T}_{lb}. \tag{6}$$

Note that when applying the Bai-Perron method for structural break testing, a small

[1] Luo and Startz (2014) undertake a Bayesian approach.

[2] For recent alternatives see e.g. Pesaran and Timmermann (2004); Eklund, Kapetanios and Price (2013); Giraitis, Kapetanios and Price (2013) and Pesaran, Pick and Pranovich (2013).

proportion of the observations at the beginning and the end of the sample needs to be trimmed. This requirement limits the immediate detection of parameter shifts when the shifts have just occurred. Therefore breaks will be identified with lags.

2.2 Forecast evaluation

We cast the model in state space form, and compute UC forecasts in line with Harvey (1989, Section 3.5), who derives multiple steps ahead forecasts using the Kalman filter. We compute one-step ahead forecasts for expanding windows, re-estimating the UC models in every step. The latest estimated unobserved components determine the forecasts, and the correlation assumptions influence the forecasts only via the estimated components. Consequently, an economic slowdown or a break in the mean of growth rate of real GDP is reflected in the forecasts with lags.

The unobserved components model provides a framework to decompose and forecast trends and cycles in GDP. However, because both trends and cycles are unobserved, we cannot evaluate and compare forecasts using forecasting errors of trends and cycles. Below we evaluate the forecasts based on alternative UC models indirectly by comparing real GDP growth rate forecasts.

3 Data

We retrieve quarterly real GDP series of the G7 countries from Thomson Reuters Datastream. The series span from 1960Q1 to 2014Q4. They are calculated using a constant price level in the local currency and seasonally adjusted. We then take the natural logarithm and multiply by 100, so that we can interpret output gaps as deviations from the long-run trend in percent. We compute quasi-real time out-of-sample forecasts from

1994Q1 to 2014Q4 which means that to forecast the trends and cycles in the period $t+1$, all past observations up to and including period t are used for estimation.

To detect drift breaks in the trend function, we compute the growth rate of real GDP (Δy_t) in percentages by taking the first difference of the natural logarithm of the real GDP series multiplied by 100. We use the Bai-Perron algorithm to detect the break dates taking 5 as the maximum number of breaks. The Bayesian Information Criterion (BIC) assists the selection of the breaks. Figures A.1 and A.2 in the Appendix display the estimated number of breaks and the last break date associated with each forecasting period for the G-7 countries, assuming a minimum distance between breaks of 0.02 times the sample length.

A striking observation is that the Global Financial Crisis (GFC) is not consistently identified in all countries in estimation samples from 2009 onwards. In France and Italy the Bai-Perron algorithm does not pick up the GFC at all, whereas in Canada and Germany the crisis is picked up in a few samples that end around 2009. Only in Japan, the U.K. and the U.S. the GFC seems to have had an impact throughout the expanding estimation samples.

4 Forecasts

Figures 1–7 show the real GDP series for the G-7 countries, together with the one-quarter ahead forecasts for real GDP, trends and output gaps. The results are based on 84 out-of-sample forecasts starting from 1994Q1 and ending at 2014Q4. We distinguish forecasts from UC models with no breaks without correlated innovations (Watson) and with correlated innovations (MNZ), and with breaks (Watson+Break and MNZ+Break).

Figure 1: One-quarter ahead forecasts of real GDP on Canada and its trends and cycles

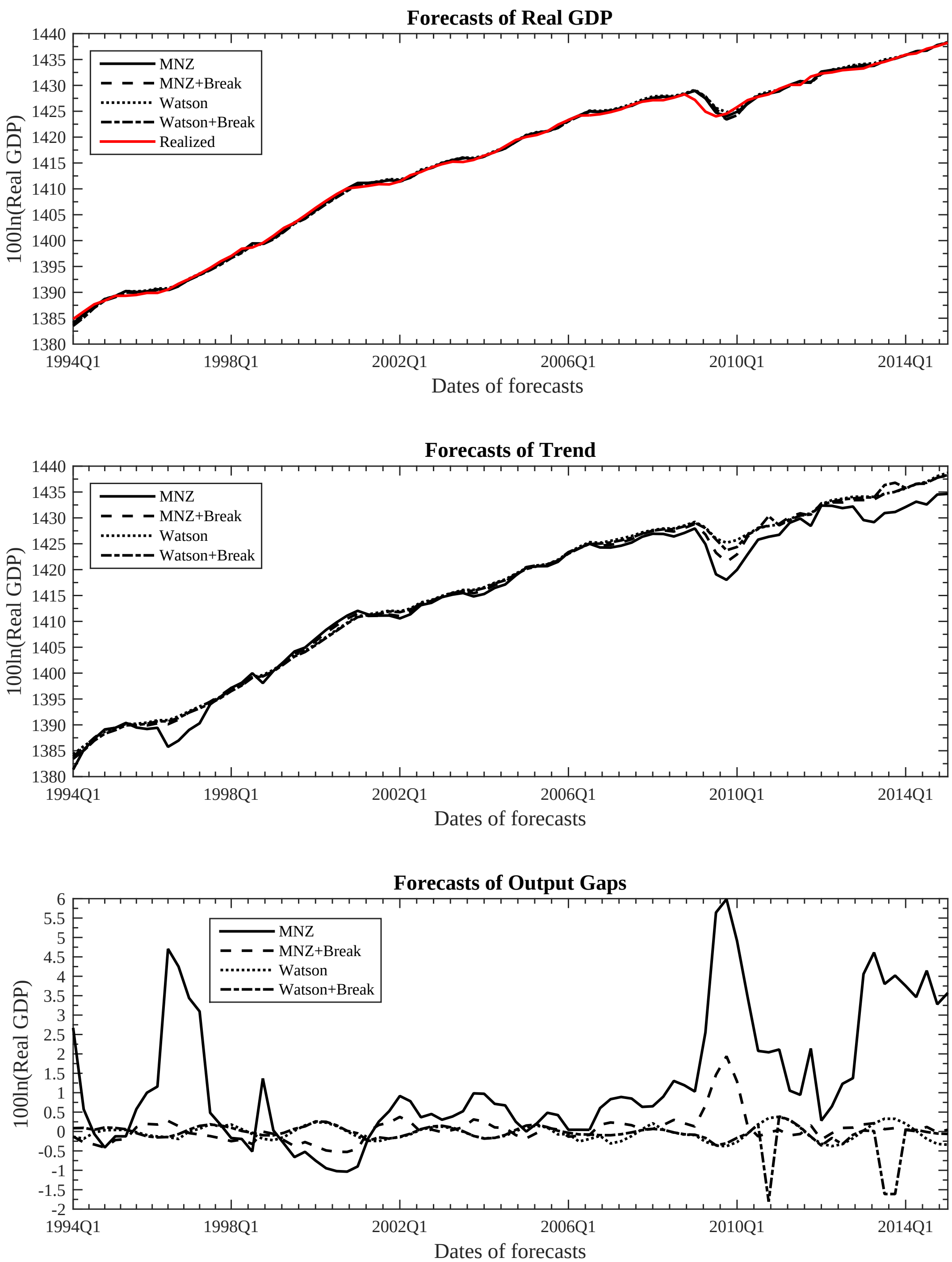


Figure 2: One-quarter ahead forecasts of the real GDP in France and its trends and cycles

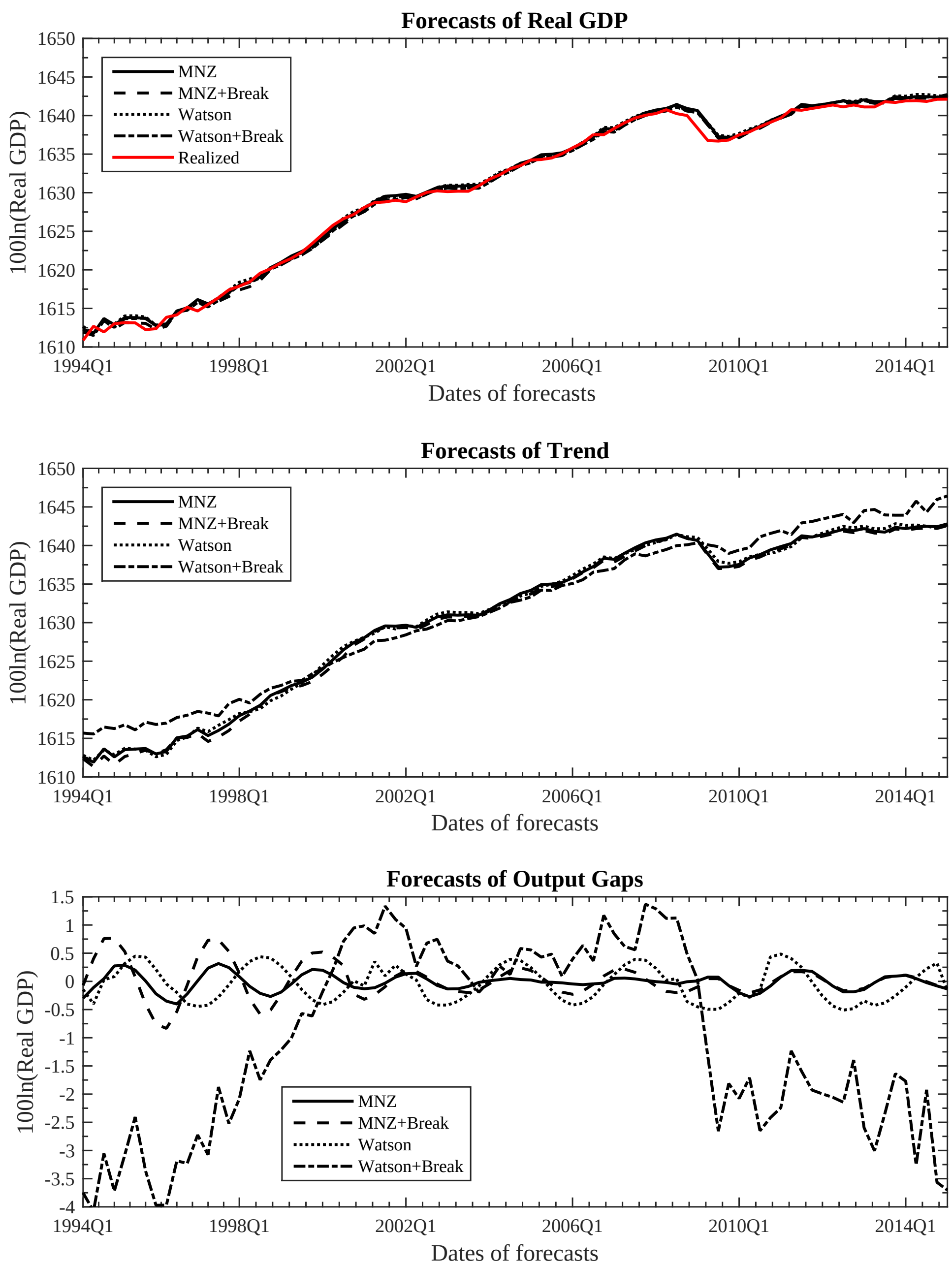


Figure 3: One-quarter ahead forecasts of real GDP in Germany and its trends and cycles

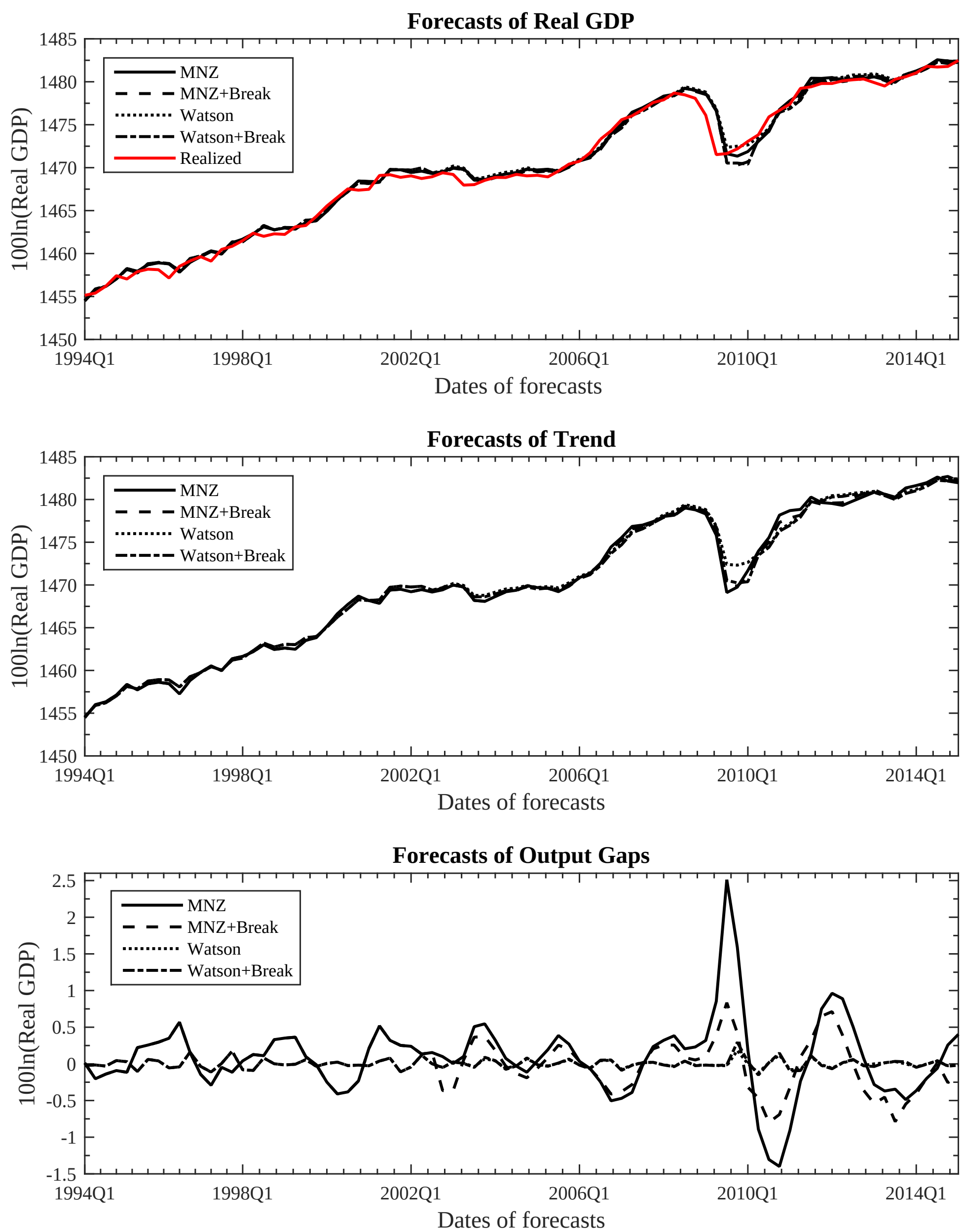


Figure 4: One-quarter ahead forecasts of real GDP in Italy and its trends and cycles

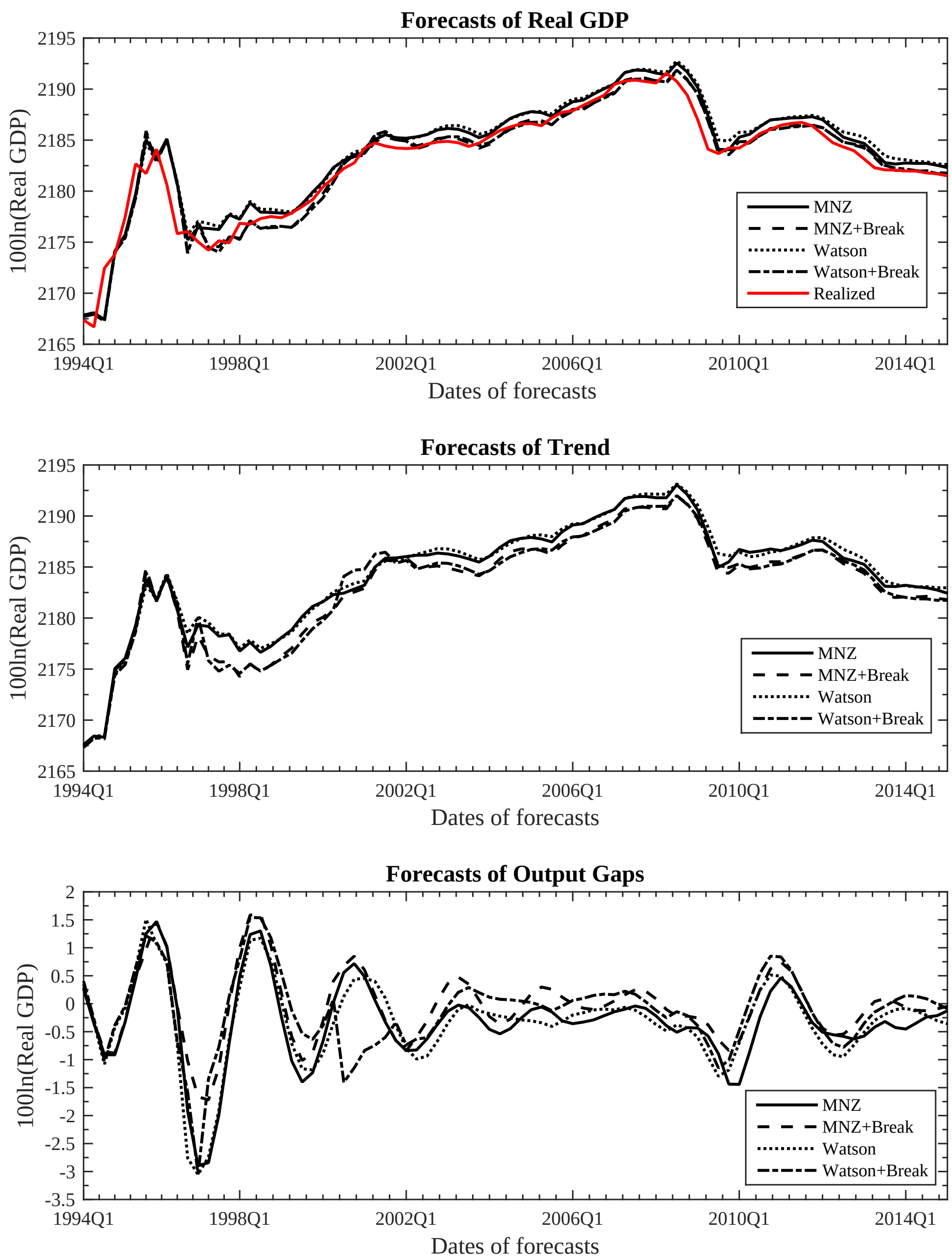


Figure 5: One-quarter ahead forecasts of real GDP in Japan and its trends and cycles

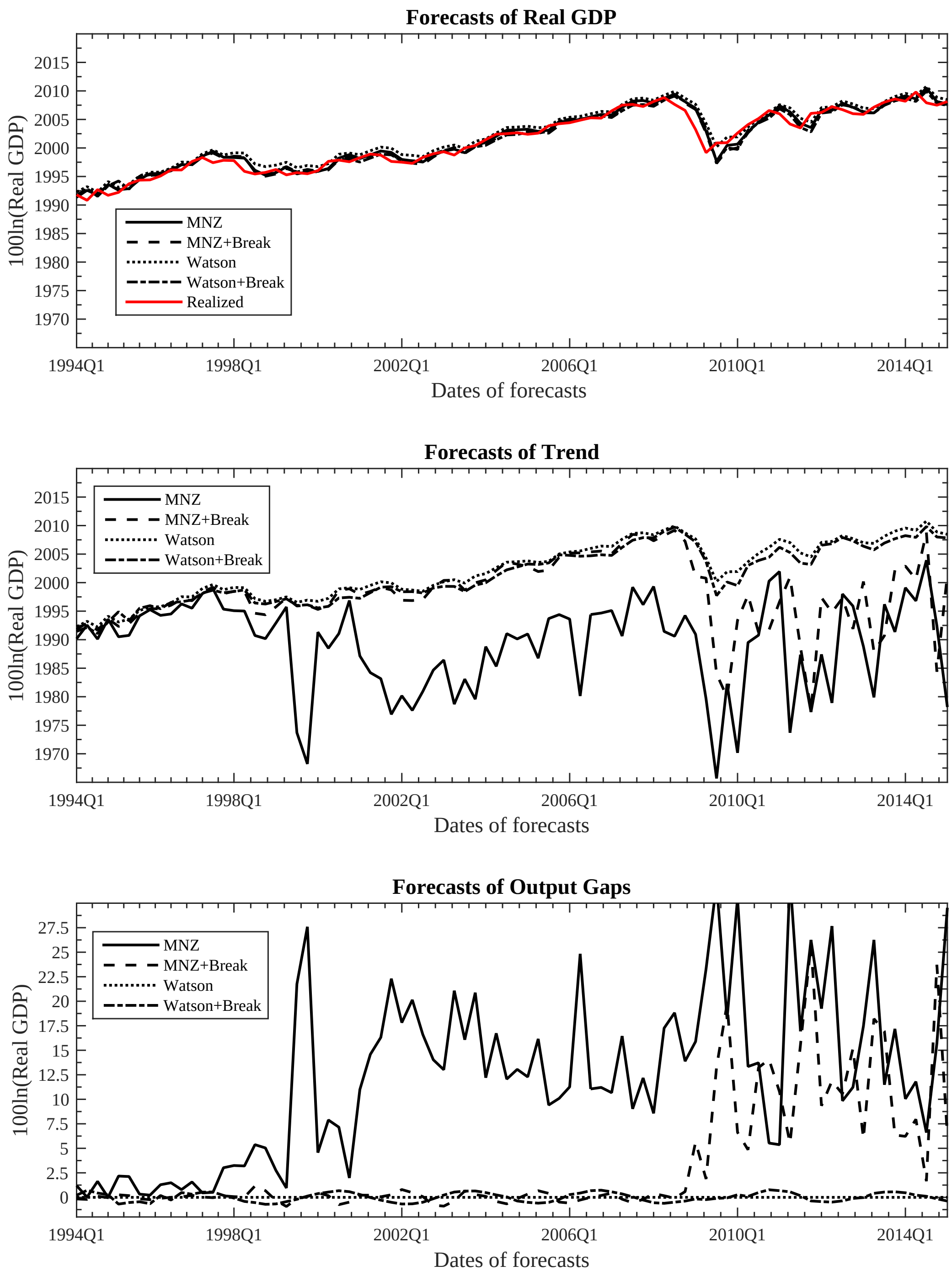


Figure 6: One-quarter ahead forecasts of real GDP in the U.K. and its trends and cycles

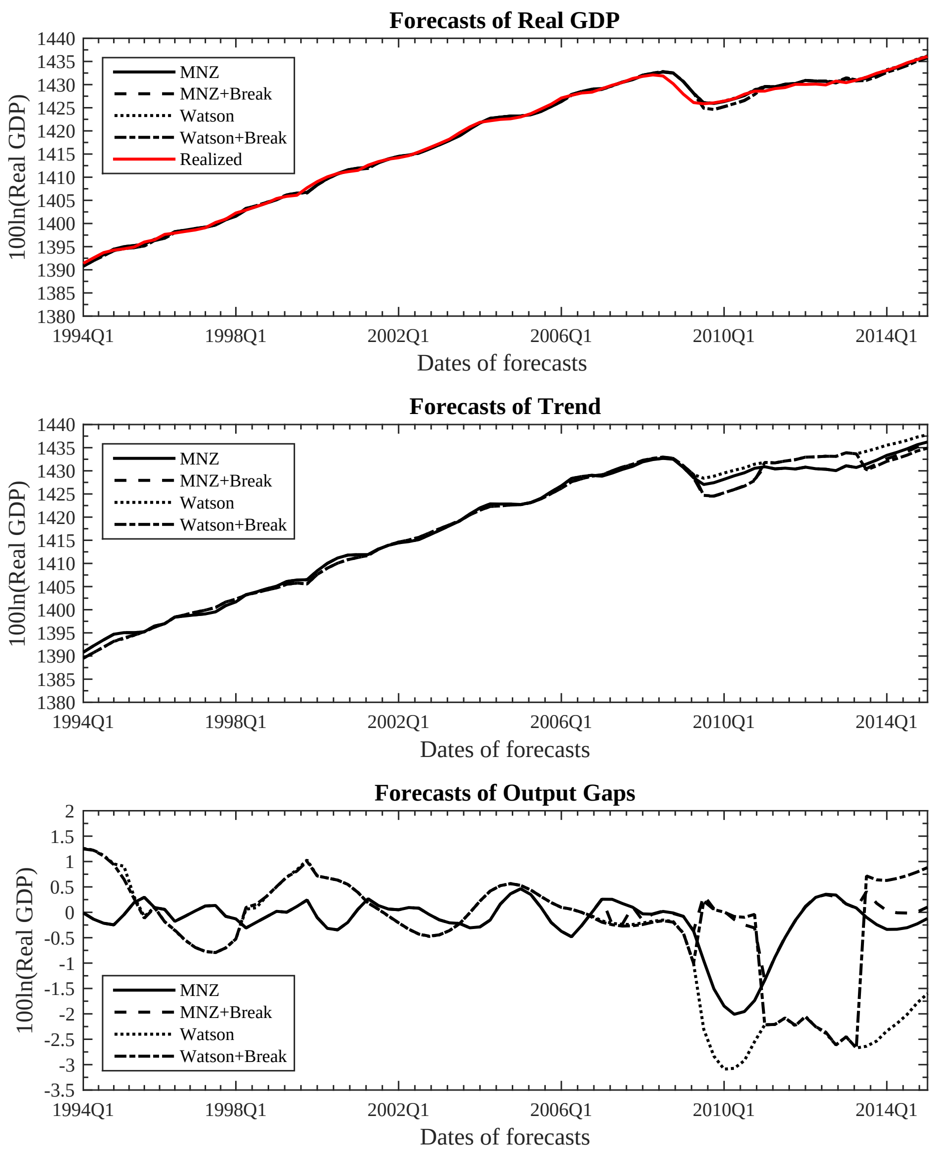
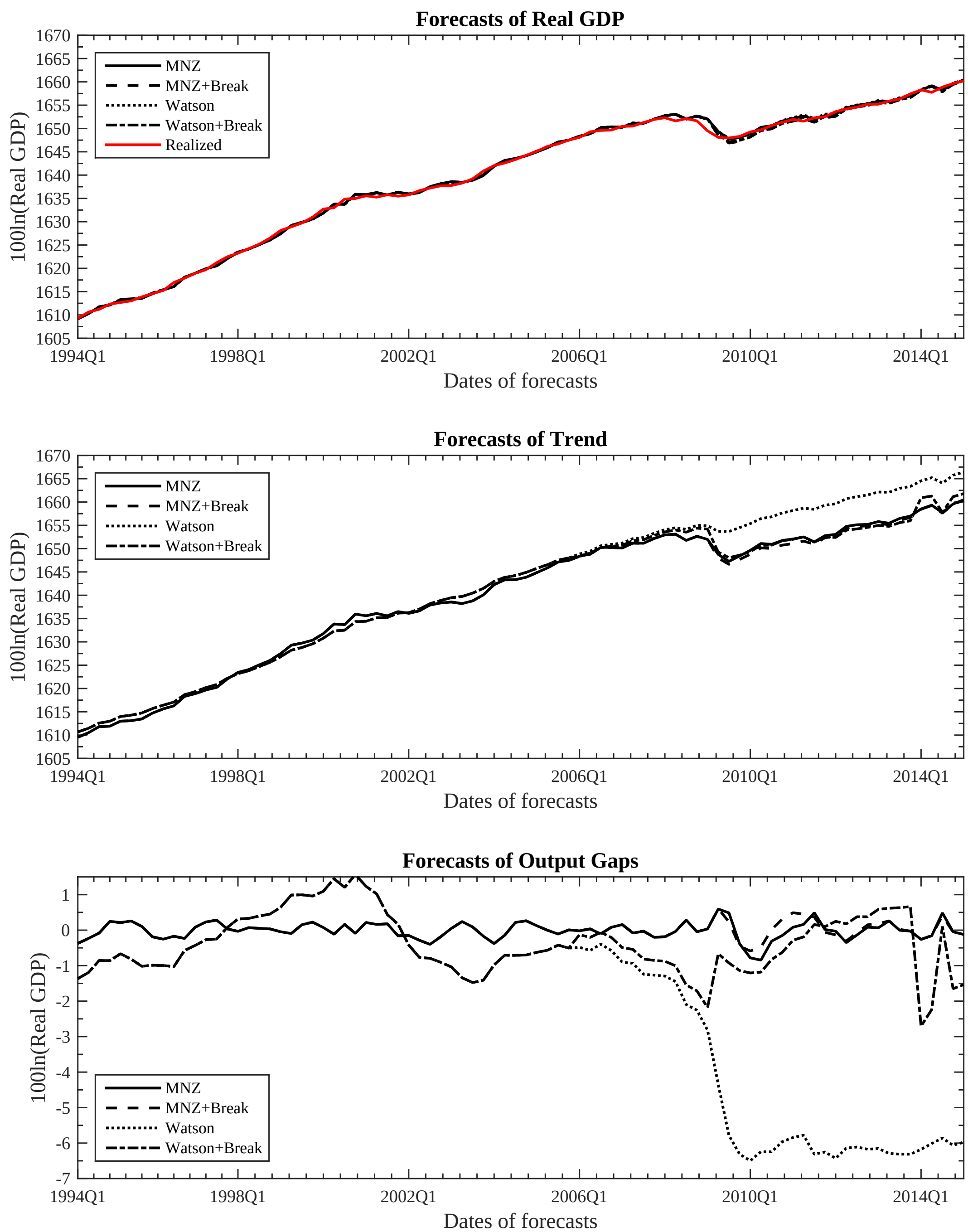


Figure 7: One-quarter ahead forecasts of real GDP in the U.S. and its trends and cycles



The alternative assumptions with respect to innovation correlation and drift break result in very different output trend and gap forecasts. For most of the G7 countries (France is the exception), restricting correlation between trend and cycle innovations to zero and incorporating no drift breaks, produces rather smooth output trend forecasts. Allowing for non-zero correlation (the MNZ results) can achieve a similar outcome in trend forecasts as models incorporating breaks. The common result is that both specifications forecast a deeper decline in output trend when the economy is experiencing recession, see for example the trend forecasts around the recent GFC periods.

Allowing for non-zero correlation yields more volatile forecasts of output gaps than imposing zero correlation for Canada, Germany and Japan. In these cases, allowing for structural breaks in the drift of the trend equation results in a "smoother" output gap forecast—see the bottom panels of each of Figures 1, 3 and 5. In contrast, in the U.K. and U.S., restricting the correlations to zero, with no drift breaks, results in more volatile output gap forecasts, but leads to smooth trend forecasts. Allowing for non-zero correlation has a similar effect to incorporating breaks, but with less pessimistic trend forecasts during recession period.

Comparing the forecasts of real GDP over different model specifications, we observe that the turning points indicated by the forecasts are generally the same, regardless of whether correlated innovations or breaks in the drifts are incorporated. However, these turning points are forecast with a delay compared to the realization. Take France in Figure 2 as an example. Although two breaks are consistently detected over the expanding samples, as shown in the Appendix, each of the models, with and without correlated shocks and/or trend breaks forecast a slowdown in GDP at the same point. The actual occurrence of this turning point is only one quarter earlier, in 2008Q1.

5 Forecast evaluation

Table 1 reports Mean Squared Forecast Errors (MSFEs) of real GDP growth rate forecasts for the G-7 countries. The AR(1) column in Table 1 shows AR(1) outcomes for comparison. At least one of the UC models produces better GDP growth rate forecasts than an AR(1) specification for four out of the seven countries—otherwise our results are consistent with existing evidence that it is difficult to empirically outperform the AR(1) model.

Table 1: Out-of-sample MSFEs for one-quarter ahead real GDP growth forecasts

	AR(1)	MNZ	MNZ+Break	Watson	Watson+Break
Canada	0.3036	0.3093	0.3101	0.3956	0.3808
France	0.4162	0.4372	0.3692	0.4795	0.3534
Germany	0.8053	0.8244	0.8848	0.8817	0.9465
Italy	2.2295	2.2780	1.7747	2.7767	1.8880
Japan	1.5886	1.3765	1.4316	2.0786	1.5402
U.K.	0.3638	0.3762	0.4975	0.3879	0.5040
U.S.	0.3627	0.3523	0.3796	0.3672	0.3675

NOTE The out-of-sample contains 84 observations from 1994Q1 to 2014Q4.

Based on the Diebold-Mariano test outcomes[3] listed in Table 2, we graphically summarize the forecasting performance of the UC models in Figure 8.

[3]We also performed the Clark-West (2007) tests for forecasts produced by nested models, and the outcomes tend to favour the largest model, MNZ+Break.

Table 2: Out-of-sample Diebold-Mariano test results for 1-quarter ahead real GDP growth forecasts

		MNZ	MNZ+Break	Watson	Watson+Break
Canada	AR(1)	-0.4213	-0.9469	-2.0162**	-1.7187**
	MNZ		-1.0640	-1.7321**	-1.7538**
	MNZ+Break			-1.0015	-1.9069**
	Watson				-0.5302
France	AR(1)	-1.3557*	-0.9261	-2.5404***	1.7540**
	MNZ		1.4075*	-1.7685**	1.9700**
	MNZ+Break			-1.8622**	0.4393
	Watson				2.7300***
Germany	AR(1)	-0.4560	-0.6725	-1.6231*	-1.0903
	MNZ		-0.7490	-1.0591	-1.2749
	MNZ+Break			0.0279	-1.7083 **
	Watson				-0.5759
Italy	AR(1)	-0.2507	3.3984***	-2.1191**	2.6818***
	MNZ		2.4543**	-3.8777***	1.7910**
	MNZ+Break			-3.3740***	-2.5922***
	Watson				2.9555***
Japan	AR(1)	2.0051**	0.9911	-2.2816**	0.2401
	MNZ		-0.7105	-3.3001***	-1.3642*
	MNZ+Break			-2.4471***	-1.0236
	Watson				2.1260**
U.K.	AR(1)	-0.4921	-1.8625**	-0.9984	-2.0921**
	MNZ		-1.6060*	-1.0046	-1.7738**
	MNZ+Break			1.4381*	-0.5068
	Watson				-1.6373*
U.S.	AR(1)	0.6607	-0.5019	-0.3398	-0.1738
	MNZ		-0.9887	-1.0743	-0.6248
	MNZ+Break			0.3836	0.9910
	Watson				-0.0100

NOTE This table reports Diebold-Mariano test statistics when the null hypothesis is that the row and column forecasts have equal predictability. A large positive statistic supports the alternative that the column forecast is better than the row forecast, while a large negative statistics supports the alternative that the row forecast is better than the column forecast. A triple asterisk, a double asterisk and a single asterisk show that the null is rejected at the 1%, 5% and 10% level of significance, respectively.

The horizontal axis presents a number of hypotheses around whether the forecasting performance of one model outperforms another according to the Diebold-Mariano tests presented in Table 2; that is the notation WB>MNZ in the first column of Figure 8 implies a test of whether the Watson specification allowing for break outperforms the MNZ without break specification. The vertical axis records whether the null hypothesis is accepted (positive) or rejected (negative) with the + signs indicating a statistically significant finding and o an insignificant finding.

Figure 8: Comparison of alternative UC models for forecasting GDP growth

NOTE. W stands for Watson; WB for Watson plus break; MNZB for MNZ plus Break.
A plus denotes a significant MSFE difference according to the Diebold-Mariano statistic at the 10% level, or better; a circle denotes an insignificant difference. Pluses and circles in the positive (negative) area indicate that the forecasts produced with the model specification before the > sign are better (worse) than forecasts produced with the other specification.

We find that taking into account correlated innovations between trend and cycle components has a positive effect on the quality of real GDP forecasts: the fourth column in Figure 8 rejects the null that Watson forecasts are better than MNZ forecasts for all countries, significantly for four countries (Canada, Germany, Japan, U.K. and U.S.). The inclusion of structural breaks seems to work for some countries (France, Italy), but not for others (Germany, U.K., U.S.). For France both MNZ and Watson models (MNZB and WB) with structural breaks produce similar quality forecasts, while for Italy the MNZ plus break model performs best. For the U.S. the MNZ type of model that allows for non-zero correlation performs better than the MNZ model plus break and the Watson models, with and without break.

6 Conclusion

This paper has studied the relative importance of including correlated trend and cycle innovations and/or structural breaks in the trend function in forecasting output trends and output gaps for G7 countries using a unobserved component framework. The one-step ahead forecasts of unobserved output trends and output gaps are evaluated indirectly from GDP growth rate forecasts.

In forecasting real GDP growth allowing for non-zero correlations (MNZ) between the trend and cycle innovations works better than assuming no correlation (Watson). Allowing for drift breaks in the trend function improves forecasts for France and Italy, but not for the other countries examined.

To conclude, we find that the forecasts of output trends and output gaps are affected by whether correlation in innovations of cycle and trend and/or drift breaks are incorporated. For most of the countries, allowing non-zero correlation between trend and cycle innovations and drift breaks results in forecasts of a deeper economic slowdown during a recession than if the model is restricted to exclude these features. The two types of restriction not only affect the magnitude of the output gaps forecasts, but also their sign. For instance, allowing for correlation between trend and cycle innovations may produce a large positive output gap forecast in the next quarter, while the model with zero correlation generates a negative output gap forecast.

Overall, in the face of uncertainty about the existence of breaks, policy makers should be cautious in restricting models to zero correlation between innovations, as we show considerable forecasting improvements can be obtained by incorporating the simple evidence on correlated shocks. Although trend breaks attract considerable interest in the *measurement* literature, in the absence of true information, it is demonstrably more important to acknowledge the potential for trend and cycle innovations to be correlated in forming GDP and output gap forecasts.

Acknowledgements

We would like to thank Todd Clark, Andrew Harvey, and the participants at the 2015 International Symposium on Forecasting, Riverside Ca, the 2015 NBP Workshop on Forecasting, Warsaw, Poland, the 'Conjunctuurdag' (Business Cycle Day) 2016, The Hague, and a seminar at the University of Tasmania for constructive comments.

References

Bai, Jushan and Pierre Perron (1998), "Estimating and testing linear models with multiple structural changes", *Econometrica*, **66**, 47–78.

Bai, Jushan and Pierre Perron (2003), "Computation and analysis of multiple structural change models", *Journal of Applied Econometrics*, **18**, 1–22.

Basistha, Arabinda and Charles R. Nelson (2007), "New measures of the output gap based on the forward-looking New Keynesian Phillips curve", *Journal of Monetary Economics*, **54**, 498–511.

Beveridge, Stephen and Charles R. Nelson (1981), "A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'", *Journal of Monetary Economics*, **7**, 151–174.

Clark, Peter K. (1987), "The cyclical component of U.S. economic activity", *The Quarterly Journal of Economics*, **102**, 797–814.

Clark, Todd E. and Kenneth D. West (2007), "Approximately normal tests for equal predictive accuracy in nested models", *Journal of Econometrics*, **138**, 291–311.

Dungey, Mardi, Jan P.A.M. Jacobs, Jing Tian, and Simon van Norden (2014), "Trend in cycle or cycle in trend? New structural identifications for unobserved components models of U.S. real GDP", *Macroeconomic Dynamics*, **19**, 776–790.

Eklund, Jana, George Kapetanios, and Simon Price (2013), "Robust forecast methods and monitoring during structural change", *The Manchester School*, **83**, 3–27.

Giraitis, Liudas, George Kapetanios, and Simon Price (2013), "Adaptive forecasting in the presence of recent and ongoing structural change", *Journal of Econometrics*, **177**, 153–170.

Harvey, Andrew C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge, UK.

Iwata, Shigeru and Han Li (2015), "What are the differences in trend cycle decompositions by Beveridge and Nelson and by Unobserved Component models?", *Econometric Reviews*, **34**, 146–173.

Kiley, Michael T. (2013), "Output gaps", *Journal of Macroeconomics*, **37**, 1–18.

Mitra, Sinchan and Tara M. Sinclair (2012), "Output fluctuations in the G-7: An unobserved components approach", *Macroeconomic Dynamics*, **16**, 396–422.

Perron, Pierre and Tatsuma Wada (2009), "Let's take a break: Trends and cycle in US real GDP", *Journal of Monetary Economics*, **56**, 749–765.

Pesaran, M. Hashem, Andreas Pick, and Mikhail Pranovich (2013), "Optimal forecasts in the presence of structural breaks", *Journal of Econometrics*, **177**, 134–152.

Pesaran, M. Hashem and Allan Timmermann (2004), "How costly is it to ignore breaks when forecasting the direction of a time series?", *International Journal of Forecasting*, **20**, 411–425.

Proietti, Tomasso (2006), "Trend-cycle decompositions with correlated components", *Econometric Reviews*, **25**, 61–84.

Watson, Mark W. (1986), "Univiate detrending methods with stochastic trends", *Journal of Monetary Economics*, **18**, 49–75.

Wieland, Volker and Maik Wolters (2013), "Forecasting and policy making", in Graham Elliott and Allan Timmermann, editors, *Handbook of Economic Forecasting*, volume 2A, Elsevier, Amsterdam, chapter 5, 239–325.

Figure A.1: Estimated number of breaks and date of last breaks in the drift of real GDP growth in Canada, France and Germany; the minimum break distance is $0.02T$

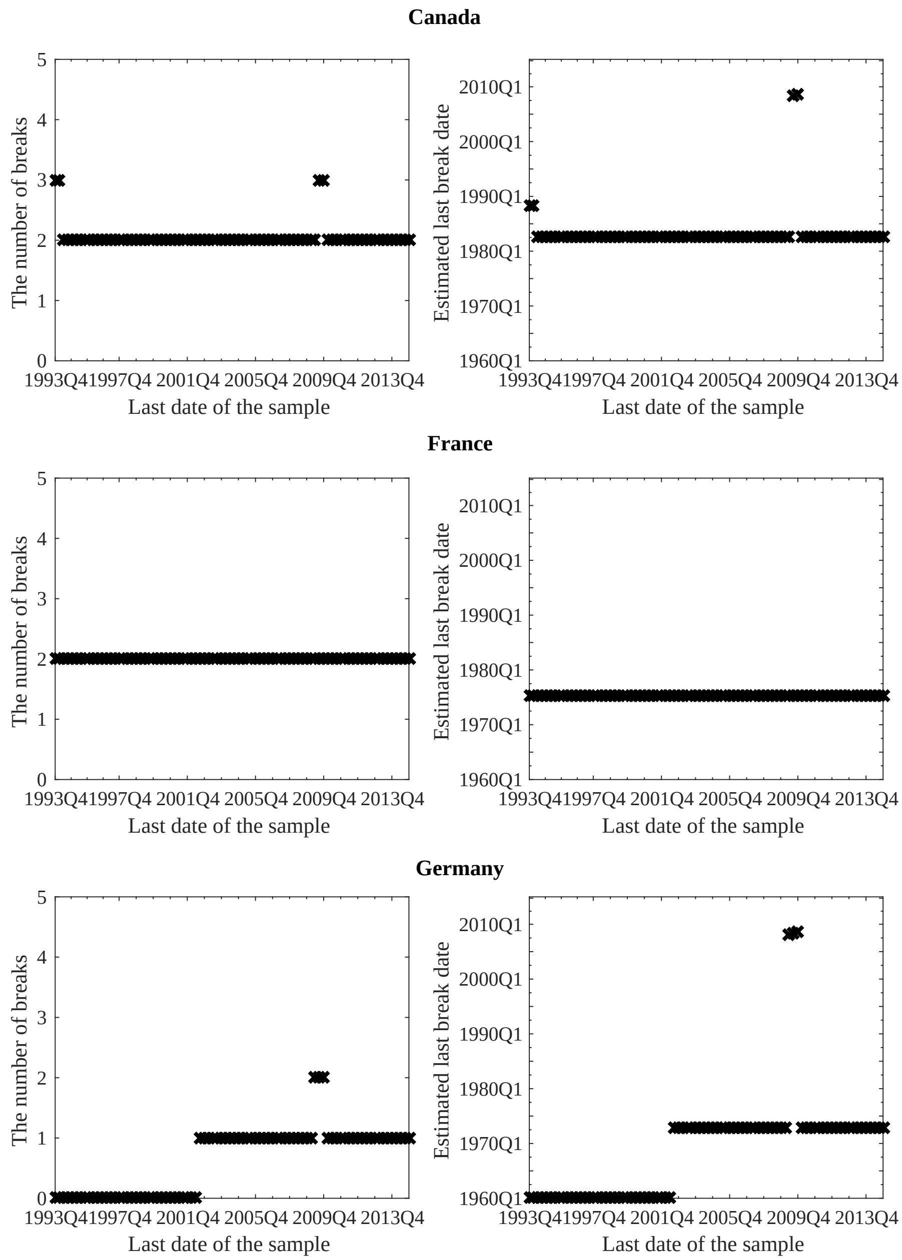
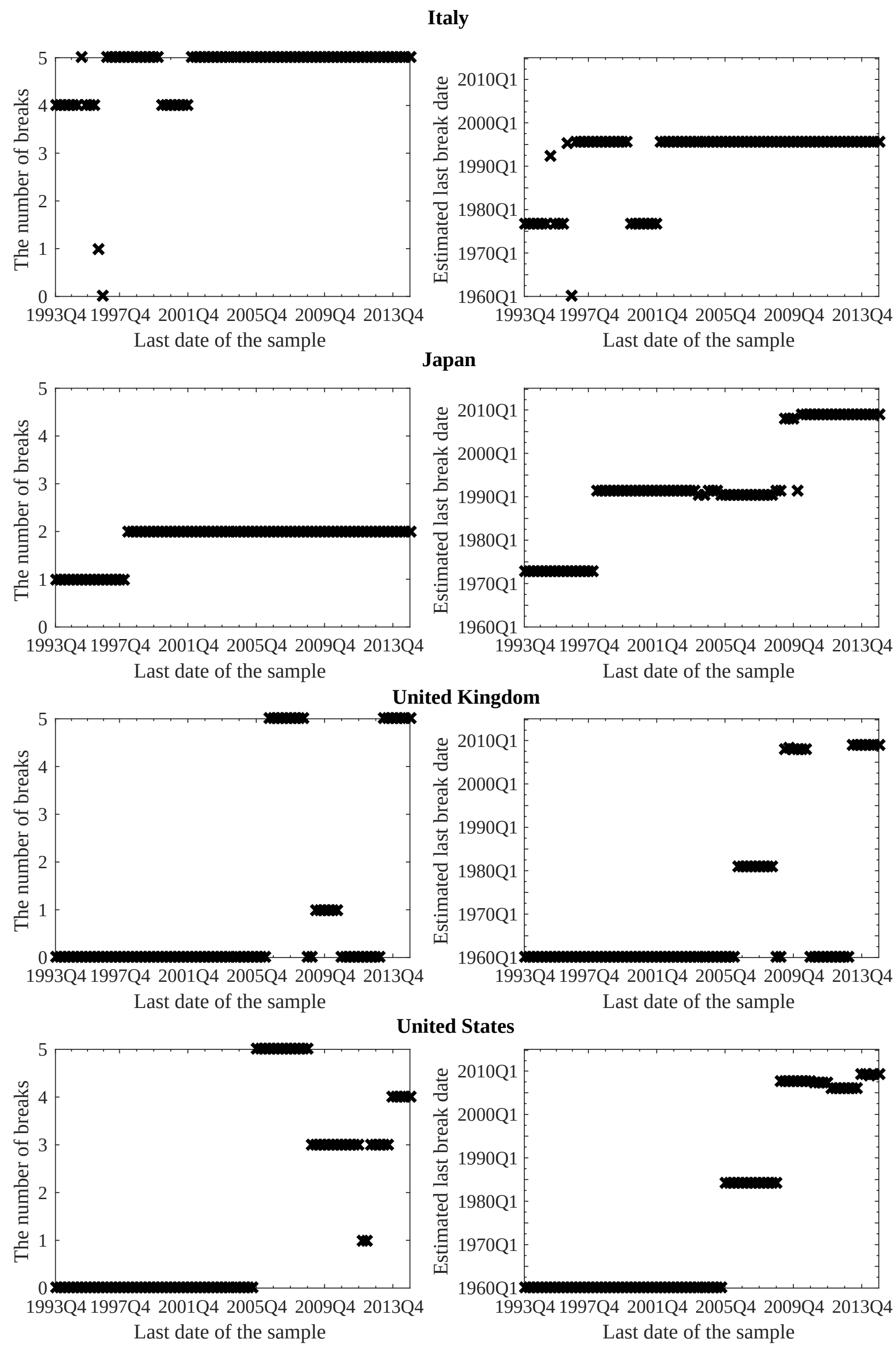


Figure A.2: Estimated number of breaks and date of last break in the drift of real GDP growth in Italy, Japan, U.K. and U.S.; the minimum break distance is $0.02T$



Tasmanian School of Business and Economics

2015-01 Surfing through the GFC: Systemic Risk in Australia, **Mardi Dungey**, Matteo Luciani, **Marius Matei**, and David Veredas

2015-02 Intra– and Inter-Village Conflict in Rural Coastal Communities in Indonesia: The Case of the Kei Islands, **Satoshi Yamazaki**, Budy Resosudarmo, Wardis Girsang, and **Eriko Hoshino**

2015-03 Turn-Taking in Finitely Repeated Symmetric Games: Experimental Evidence, **Hugh Sibly**, **John Tisdell**, and Shuan Evans

2015-04 High Frequency Characterization of Indian Banking Stocks, **Mohammad Abu Sayeed**, **Mardi Dungey**, and **Wenying Yao**

2015-05 The Role of Intra-day Volatility Pattern in Jump Detection: Empirical Evidence on How Financial Markets Respond to Macroeconomic News Announcements, **Wenying Yao** and **Jing Tian**

2015-06 Understanding the Deviations of the Taylor Rule: A New Methodology with an Application to Australia**,** Kerry Hudson and **Joaquin Vespignani**

2015-07 A New Monthly Indicator of Global Real Economic Activity, Francesco Ravazzolo and **Jaquin Vespignani**

2015-08 The Macroeconomic Effects of Oil Price Shocks on ASEAN-5 Economies, **Mala Raghavan**

2016-01 Global Uncertainty and the Global Economy: Decomposing the Impact of Uncertainty Shocks, Wensheng Kang, Ronald A Ratti and **Joaquin Vespignani**

2016-02 The Implications of Liquidity Expansion in China for the US Dollar, Wensheng Kang, Ronald A Ratti and **Joaquin Vespignani**

2016-03 The Impact of Oil Price Shocks on the US Stock Market: A Note on the Roles of US and non-US Oil Production, Wensheng Kang, Ronald A Ratti and **Joaquin Vespignani**

2016-04 Forecasting Output Gaps in the G-7 Countries: The Role of Correlated Innovations and Structural Breaks, **Mardi Dungey**, Jan P.A.M. Jacobs and **Jing Tian**

UNIVERSITY of TASMANIA AUSTRALIA