



DP2006/01

Phillips curve forecasting in a small open economy

Troy Matheson

March 2006

JEL classification: C53, E31

www.rbnz.govt.nz/research/discusspapers/

Discussion Paper Series

DP2006/01

Phillips Curve Forecasting in a Small Open Economy*

Troy Matheson[†]

Abstract

Stock and Watson (1999) show that the Phillips curve is a good forecasting tool in the United States. We assess whether this good performance extends to two small open economies, with relatively large tradable sectors. Using data for Australia and New Zealand, we find that the open economy Phillips curve performs poorly relative to a univariate autoregressive benchmark. However, its performance improves markedly when sectoral Phillips curves are used which model the tradable and non-tradable sectors separately. Combining forecasts from these sectoral models is much better than obtaining forecasts from a Phillips curve estimated on aggregate data. We also find that a diffusion index that combines a large number of indicators of real economic activity provides better forecasts of non-tradable inflation than more conventional measures of real demand, thus supporting Stock and Watson's (1999) findings for the United States.

* The views expressed in this paper are those of the author(s) and do not necessarily reflect the views of the Reserve Bank of New Zealand. I thank Dean Ford, Tim Hampton, Markus Hyvonen, and Giancarlo La Cava for their help with the Australian data. I also thank various members of the Economics Department of the Reserve Bank of New Zealand for useful comments, particularly Kirdan Lees, Christie Smith, and Shaun Vahey.

[†] Troy Matheson, Economics Department, RBNZ, P.O.Box 2498, Wellington, New Zealand, Tel: +64-4-471-3859; Fax +64-4-473-1209; *email address: troy.matheson@rbnz.govt.nz*

©Reserve Bank of New Zealand

1 Introduction

Conceptually, goods and services can be characterised as being either tradable or non-tradable. Tradable goods and services are traded internationally and have prices that are, at least in part, determined in world markets. Non-tradable goods and services, on the other hand, have prices that can be characterised as being determined domestically. Tradable and non-tradable prices have been shown to display different time series properties (De Gregorio *et al* 1994 and Engel 1999). Indeed, a feature of recent open economy macroeconomic models is that they either distinguish between the inflation processes of domestically produced goods and imports (see Gali and Monacelli 2005, Monacelli 2005 and Guender 2005) or the inflation processes of the tradable and non-tradable sectors (Laxton and Pesenti 2003 and Devereux *et al* 2005).

While there is much empirical work exploring the forecasting performance of the Phillips curve in the US (for example, Stock and Watson 1999, Clark and McCracken 2005 and Orphanides and van Norden 2005), research examining its performance in open economies is more scarce. The open economy research that does exist does not explicitly account for the sectoral differences that result from trade (Robinson *et al* 2003 and Batini *et al* 2005, for example). Yet, theory on the aggregation of economic series dating back to Theil (1954) shows that there can be efficiency gains from formally modelling these sectoral differences. Grunfeld and Griliches (1960), for example, showed that combining estimates from correctly specified disaggregate models produces a mean squared error no larger (and possibly smaller) than an aggregate model estimated directly. If the disaggregate equations are mis-specified, however, the aggregate specification may be preferable, leaving it an empirical question as to which method should be used in practice.¹ This paper adds to previous empirical work by considering a sectoral approach to forecasting inflation with the Phillips curve.

We examine the forecasting performance of an aggregate open economy Phillips curve for both Australia and New Zealand. Over a variety of definitions for real demand and international competitiveness, we find that the open economy Phillips curve generally forecasts poorly. However, when we combine forecasts from sectoral Phillips curves for the non-tradable and tradable sectors, the forecasting performance of the Phillips curve improves markedly. We also find that a diffusion index combining a large number of indicators of real economic activity provides

¹ Hubrich (2005) includes a summary of the literature relating to the topic of aggregation versus disaggregation in econometrics.

the best forecasts of non-tradable inflation across both countries, supporting the findings of Stock and Watson (1999).

The paper proceeds as follows. Section 2 describes the conventional closed economy Phillips curve and its open economy analogue. We then describe our sectoral approach to forecasting with the open economy Phillips curve. Our data and our forecasting experiment are outlined in sections 3 and 4. We evaluate the Phillips curve forecasts against autoregressive benchmarks in section 5. Section 6 compares forecasts from the sectoral Phillips curve (weighting the closed economy Phillips curve forecast and the open economy Phillips curve forecast) with aggregate Phillips curve forecasts. We conclude in section 7.

2 The Phillips curve

The general closed economy Phillips curve specification used by Stock and Watson (1999), Stock and Watson (2003) and Clark and McCracken (2005) for the US is:

$$\pi_{t+h} - \pi_t = \phi + \beta(L)x_t + \gamma(L)\Delta\pi_t + e_{t+h}, \quad (1)$$

where $\pi_{t+h} = \ln(P_{t+h}/P_t)$ is h -period inflation in the price level P_t and $\pi_t = \ln(P_t/P_{t-1})$; x_t is a measure of real demand (or costs) in the economy; and $\beta(L)$ and $\gamma(L)$ are polynomials of the lag operator L (see Clarida, Gali, and Gertler 1999 for an exposition of a closed economy Phillips curve in the New Keynesian framework).

Importantly, equation (1) implies that inflation is integrated of order one $I(1)$ – meaning that prices are $I(2)$. While this is a standard assumption for empirical work regarding the aggregate price level in the US and the euro area (see Marcellino *et al* 2003), it is less conventional in inflation targeting open economies, where inflation is widely regarded as being $I(0)$. Nevertheless, eq1 can readily be adapted to model $I(1)$ prices by modeling inflation in levels rather than in changes, as in Orphanides and van Norden (2005):

$$\pi_{t+h} = \phi + \beta(L)x_t + \gamma(L)\pi_t + e_{t+h}. \quad (2)$$

2.1 Open economy considerations

In an open economy, inflation is not only determined by domestic economic conditions but also by developments amongst the economy's trading partners, which

influence the competitiveness of the tradable sector. The closed economy Phillips curve is thus typically augmented with variables that capture the impact of swings in international competitiveness. The simplest way to do this is by including nominal exchange rate terms into equation (2). Alternatively, the real exchange rate (Svensson 2000 and Guender 2005), the terms of trade (Gali and Monacelli 2005), deviations from the law of one price (Monacelli 2005), and the domestic currency price of imports (Batini *et al* 2005), are all valid candidate measures of international competitiveness.

Capturing the impact of deviations in international prices suggests the following open economy analogue to the closed economy Phillips curve:

$$\pi_{t+h} = \phi + \beta(L)x_t + \delta(L)s_t + \gamma(L)\pi_t + e_{t+h}, \quad (3)$$

where s_t is a measure of the tradable sector's international competitiveness.²

While this aggregate specification can be estimated directly, there may be a more efficient estimation strategy. As mentioned in the introduction, the data generating processes of prices in the tradable and non-tradable sectors have been shown to differ (De Gregorio *et al* 1994 and Engel 1999). Certainly, this is the case in Australia and New Zealand, where non-tradable inflation has a higher mean, a lower standard deviation and is negatively correlated with tradable inflation, see Table 1. In addition to improving our understanding about the nature of the aggregate inflation process, Grunfeld and Griliches (1960) show that a sectoral approach to estimation can produce more efficient estimates. It thus seems reasonable to formally articulate sectoral differences when forecasting aggregate inflation.

To specify different Phillips curves for the non-tradable and tradable sectors, consider the key drivers of inflation in each sector of the economy. When an economy is closed, no goods and services are traded internationally – they are *all* non-tradable. The obvious choice for a non-tradable inflation π^N specification is thus the closed economy Phillips curve:

$$\pi_{t+h}^N = \phi + \beta(L)x_t^N + \gamma(L)\pi_t^N + e_{t+h}. \quad (4)$$

where non-tradable inflation is driven by x_N , real economic activity in the non-tradable sector, and by lags of non-tradable inflation.

² Some readers may wonder why we refer to s_t generally, as a measure of international competitiveness, and not as exchange rate pass-through. We do this to be explicit about the nature of goods and services produced by the tradable sector: import price pass-through relates to imported goods and services only, whereas the tradable sector actually encompasses *both* exports and imports.

Table 1
Summary statistics – annual inflation 1992Q1 to 2005Q2

Australia	CPI	Tradable	Non-tradable
Mean	2.45	1.83	3.00
Standard deviation	0.64	1.17	0.79
Weight in CPI		0.47	0.53
Correlation (tradable/non-tradable)			-0.18
NZ			
Mean	2.06	0.76	3.11
Standard deviation	0.62	1.49	1.06
Weight in CPI		0.44	0.56
Correlation (tradable/non-tradable)			-0.49

The more competitive the economy is with the rest of the world, the faster changes in world prices and the exchange rate will impact on prices in the tradable sector. Indeed, in a perfectly competitive world, domestic tradable prices will adjust immediately and fully to changes to world prices and the exchange rate – making international prices important drivers of inflation in the tradable sector. Notwithstanding swings in international competitiveness, demand conditions will also influence inflation in the tradable sector, as in the economy more generally. Thus, inflation in the tradable sector will be guided by both fluctuations in international competitiveness and demand conditions. This makes the open economy Phillips curve (3) a natural choice for an empirical model of inflation in the tradable sector π^T :

$$\pi_{t+h}^T = \phi + \beta(L)x_t^T + \delta(L)s_t + \gamma(L)\pi_t^T + e_{t+h}. \quad (5)$$

where tradable inflation is driven by x_T , real economic activity in the tradable sector, a measure of the tradable sector's international competitiveness s_t , and lags of tradable inflation.

Note that weighting together forecasts from equations (4) and (5) yields a combined forecast for aggregate inflation:

$$\pi_{t+h} = \alpha\pi_{t+h}^T + (1 - \alpha)\pi_{t+h}^N \quad (6)$$

where α is the size of the tradable sector in the open economy (a measure of the economy's openness).

Clearly, it is not ideal to assume that the non-tradable and tradable sectors are independent of one another. After all, there will always be a finite non-tradable component to the production and distribution of a tradable goods – there are no purely tradable goods, just goods that are more subject to international developments than others. Acknowledging this, we assume that real demand is proportional across the non-tradable and tradable sectors, $x_t^N \propto x_t^T$, and use real aggregate demand x_t to estimate (4) and (5), i.e. we let $x_t^N = x_t^T = x_t$. It is then an empirical question whether the aggregate Phillips curve produces better forecasts than the sectoral approach (forecasting the tradable and non-tradable sectors separately and then aggregating the forecasts). We evaluate the forecasting performance of each of the Phillips curves described above, allowing several definitions of real demand x_t and international competitiveness s_t .

3 Data

We use quarterly data for Australia and New Zealand from 1992Q1 to 2005Q2.³ The price level P_t is defined to be the consumers price index (CPI) excluding interest charges. Tradable and non-tradable prices are defined to be the tradable and non-tradable sub-indices of the CPI in both countries: note that Australia and New Zealand are unique internationally because their national statistical agencies publish tradable and non-tradable price indexes on a quarterly basis.⁴ Taxes are excluded from the Australian CPI data, thus avoiding the imposition of a goods and services tax in 2000. Likewise, the impact of a change in the way rents were measured in 2001Q1 is excluded from the CPI in New Zealand.⁵ We use implicit weights to weight the tradable and non-tradable indexes for the sectoral forecast.⁶

We use several definitions of real demand x_t : real GDP; total employment; the unemployment rate; capacity utilisation; and a diffusion index. The diffusion index is calculated as the first principal component from a large set of indicators of

³ The sample period covers the period in which New Zealand has been targeting inflation, after allowing for a period of transition to low inflation.

⁴ The classification of an item as a tradable or a non-tradable is conducted in two steps: the first step mechanically identifies the goods and services that have significant tradable components from input-output tables; the second step classifies the remaining items using a more subjective approach (see www.stats.govt.nz for a more detailed description of the classification algorithm).

⁵ This adjustment is made by constructing indexes that exclude the rent index in 2001Q1.

⁶ An implicit weight adjusts for the relative growth in the sub-indices that has occurred since the base year.

real economic activity (see Stock and Watson 1999 and Stock and Watson 2002). The data included in the diffusion index are identified in appendices A and B. Of these variables real GDP, total employment, and the unemployment rate require de-trending.⁷ Because our results will likely be sensitive to how the data are filtered (Canova 1998), we de-trend these variables using a variety of filters: (log) first differences, and both a one-sided and a two-sided Hodrick and Prescott (HP) filter.⁸ Note that the unemployment rate is not logged before differences are taken.

In addition to these measures of real demand, we also look at the Reserve Bank of New Zealand's (RBNZ) real-time measure of the output gap, constructed using a multivariate filter (see Conway and Hunt 1997). No comparable output gap estimate is available for Australia.

We use the nominal trade weighted index and import prices as measures of the international competitiveness of the tradable sector of the economy s_t . We take (log) first differences of both these series.

4 Simulated out-of-sample forecast comparisons

To simulate the forecasting performance of our empirical models, we extract all trends and estimate all equations recursively for each quarter from 1999Q4 to 2005Q1. The RBNZ's real-time output gap estimates are those that underpinned the projections published in the Bank's quarterly *Monetary Policy Statements* over the out-of-sample period. The out-of-sample forecasting performance of the models is then evaluated at horizons h of 2, 4 and 8 quarters ahead using ex-post inflation data from 2000Q1 to 2005Q2.

We first evaluate the aggregate Phillips curve (3), the non-tradable Phillips curve (4), and the tradable Phillips curve (5) against autoregressive benchmarks, and then we assess whether forecasting with the aggregate Phillips curve (3) is better than forecasting with the combined sectoral Phillips curves (6). The orders of the lag polynomials are chosen recursively for all Phillips curves using the Schwartz-Bayesian Information Criterion (BIC), where the order of the lag polynomial L can range from 1 to 4.

⁷ Following significant labour market reform in both countries over the 1990s, the unemployment rate level has a pronounced downward trend over our sample.

⁸ The one-sided filter preserves the temporal ordering of the data, whereas the two-sided filter yields data that are subject to revision. The raw series that are HP-filtered begin in 1980Q1 to avoid the problems associated with identifying trends at the beginning of the sample.

5 Testing against an autoregressive benchmark

It is commonplace to compare forecasting performance against a parsimonious benchmark – typically a univariate autoregression (AR) or a random walk. Our benchmark is the iterated forecast from a one step ahead AR(1) model.⁹ As a robustness check for our benchmark, we initially compare it to four other univariate forecasts: a standard random walk (where the last observation is taken as the forecast at all horizons), a random walk on the mean (where the sample mean of the series is taken as the forecast at all horizons), and two recursive AR forecasts (where the number of lags can range between 1 and 4 each quarter, and are chosen by either the Akaike information criterion, AIC, or the BIC) The AR(1) benchmark performs well relative to the other univariate forecasts (see appendix C).

Following Diebold and Mariano (1995) and West (1996), we can test the null hypothesis that models i and j (the autoregressive benchmark) have equal forecast accuracy. Specifically, squared forecast errors are constructed for each model:

$$\varepsilon_{i,t+h} = (\pi_{t+h}^k - \hat{\pi}_{i,t+h}^k)^2 \quad (7)$$

where π_{t+h} is inflation at horizon h and $\hat{\pi}_{i,t+h}^k$ is a prediction of type- k inflation from model i at time t , with $k = (\text{aggregate, non-tradable, tradable})$. The squared forecast errors are then differenced $d_t = \varepsilon_{j,t+h} - \varepsilon_{i,t+h}$, producing a series of squared error differentials $\{d_t\}_{t=1}^T$, where $T = ((T_2 - h) - T_1)$, and T_1 and $T_2 - h$ are the first and last dates over which the out-of-sample forecasts are made, respectively.

However, when $\beta(L)$ and $\delta(L) = 0$ and $\gamma(1)$, our null and alternative models are the same – the models are nested. In this situation, the distribution of d_t is non-standard (Clark and McCracken 2001). Thus far, the distribution theory related to testing mean squared forecast error (MSFE) differences in nested models is limited to a few special cases (see Clark and McCracken 2001 and Clark and West 2005b, for example). Clark and West (2005a) propose a bias adjustment to the mean square error differences, and show that this adjusted statistic can be tested using standard methods. We use this adjusted statistic to test for equal forecast accuracy between our AR(1) benchmarks and the Phillips curves. The

⁹ Using a large number of US time series, Marcellino *et al* (2005) show that an iterated AR forecast generally outperforms a direct AR forecast, the AR analogue to our directly estimated Phillips curves.

adjusted statistic d_t^* is simply the sample average of:¹⁰

$$d_t^* = d_t + (\hat{\pi}_{j,t+h}^k - \hat{\pi}_{i,t+h}^k)^2 \quad (8)$$

We can then test the hypothesis that model i has better forecasting accuracy than model j using a standard t -test – evaluating whether the difference in adjusted MSFEs is significantly greater than zero, $E_t[d_t^*] > 0$.¹¹ To ease interpretation, we display unadjusted MSFE ratios rather than adjusted MSFE differences in the results tables, where a number greater than 1 indicates a lower MSFE (better forecasting performance) from model j , the autoregressive benchmark.

The forecasting results for the aggregate Phillips curve relative to the autoregressive benchmark are displayed in appendix D. The autoregressive benchmark produced lower MSFEs in the vast majority of cases. In fact, for New Zealand, not a single Phillips curve forecast outperformed the benchmark on an unadjusted basis. The results are slightly more positive for Australia, where forecasts that use GDP outperformed the benchmark at some shorter horizons. Likewise, capacity utilisation produced better forecasts than the benchmark at shorter horizons in Australia. The best Phillips curve forecast in Australia used GDP growth and the TWI, while no Phillips curve emerged as dominant in New Zealand. Phillips curves that incorporated the RBNZ’s real-time assessment of the output gap yielded broadly similar forecasting performance to the other measures of real demand.

The forecasting performance of the tradable and non-tradable Phillips curves is displayed in appendices E and F. Focussing first on appendix E, we find that the non-tradable Phillips curve routinely outperformed the autoregressive benchmark in New Zealand, and it performed well in some cases in Australia. Generally speaking, the best forecasting models across both countries included GDP, capacity utilisation or the diffusion index. The forecasting performance of the diffusion index was particularly impressive in New Zealand. It also produced the best forecasts for non-tradables inflation one year ahead in Australia. The Phillips curves that utilised the RBNZ’s real-time output gaps produced forecasts that were broadly comparable with the other measures of real demand.

Turning to the performance of the tradable models (appendix F), we find that the autoregressive benchmark was only bettered in some cases. As with the results

¹⁰ The statistic adjusts the MSFE of the alternative model down, to account for the noise introduced through the unnecessary estimation of parameters if the null hypothesis is true.

¹¹ We estimate the variance of the mean difference in squared forecast errors using the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) estimator, with a truncation lag of $(h - 1)$, and compare the test statistic to a Student- t distribution with $(T - 1)$ degrees of freedom.

for non-tradable inflation, the best forecasts tend to use GDP, although the specifications that use the change in the unemployment rate also perform quite well. Phillips curves that use the TWI generally perform better than those using import prices in Australia. Yet, there is no consensus on which measure of international competitiveness was best in New Zealand. Similar to the results for the aggregate and non-tradable Phillips curves, the RBNZ's real-time output gaps generally yields comparable forecasting performance to the other measures of real demand.

6 Testing the sectoral approach

Is it better to forecast using the aggregate Phillips curve forecast, or is the combined forecast from the sectoral Phillips curves better? Conceptually, this can be tested using the same methods as above – comparing the MSFE difference between the two forecasts. However, because of the recursive lag length selection in our models, at some dates the aggregate and combined models are nested and at some dates they are not, making the bias adjustment inappropriate. For this reason, we report the relative MSFEs, and do not report the statistical significance of the MSFE differentials.

The encompassing test proposed by Chong and Hendry (1986) remains asymptotically valid in this situation (Clark and McCracken 2001). Thus, we can test whether model i 's inflation forecast adds information to the forecast from model j : a positive correlation between the forecast error from using model j (the aggregate Phillips curve) and the forecast from model i (the sectoral Phillips curve) indicates informational content in model i that adds to the forecasting capability of model j . The encompassing test is constructed in a very similar fashion to the test of equal forecast accuracy, where model j 's forecast error is constructed:

$$v_{j,t+h} = \hat{\pi}_{t+h}^k - \hat{\pi}_{j,t+h}^k \quad (9)$$

and then the sequence $\{v_t\}_{t=1}^T$ is regressed on model i 's forecasts: the resulting coefficient estimate is tested in the same way as d_t^* from above.

Appendix G contains the out-of-sample forecasting performance of the sectoral Phillips curve relative to the aggregate Phillips curve. The results are striking. In all but a handful of cases, the sectoral forecasts outperform the aggregate forecasts according to MSFE comparisons. The value of the sectoral forecast is further confirmed by the encompassing test, which indicates that all but a few of the sectoral forecasts have predictive power over and above the corresponding aggregate

forecasts at the 10 per cent level. Moreover, most of the forecasts that fail the encompassing test have lower MSFEs than the corresponding aggregate forecasts.

Given the poor performance of the aggregate Phillips curve relative to the autoregressive benchmark, the improvement that came with using the sectoral Phillips curve perhaps comes as no surprise. The sectoral Phillips curves outperform the benchmark in the majority of cases at the short horizon (appendix H). However, its performance is generally better in New Zealand than it is in Australia, echoing the poor Phillips curve forecasting results obtained by Robinson *et al* (2003) for Australia. Nevertheless, while outside the scope of the current paper, it may be possible to make further forecast improvements by combining forecasts from sectoral Phillips curves that use different measures of real demand (say, a diffusion index in the non-tradable Phillips curve and GDP growth in the tradable Phillips curve), or by using variants of the empirical models used here (such as models that exclude AR terms).

7 Conclusion

Several findings emerge from our empirical results. First, across a range of different definitions of real demand and international competitiveness, the aggregate open economy Phillips curve generally produces poor forecasting performance relative to an autoregressive benchmark. Second, we find that combining sectoral forecasts from closed economy Phillips curves for the non-tradable sector and from open economy Phillips curves for the tradable sector produces better forecasts than the aggregate open economy Phillips curves. This suggests that, in addition to facilitating understanding about the inflation process, a sectoral approach to forecasting inflation with the Phillips curve is preferable to the aggregate approach in an open economy. Our third finding is that, across both Australia and New Zealand, a diffusion index that combines a large number of indicators of real economic activity provides better forecasts of non-tradable inflation than more conventional measures of real demand, supporting the findings of Stock and Watson (1999) for the United States.

References

- Batini, N, B Jackson, and S Nickell (2005), "An open-economy new Keynesian Phillips curve for the U.K.," *Journal of Monetary Economics*, 52,

1061–1071.

- Canova, F (1998), “Detrending and business cycle facts,” *Journal of Monetary Economics*, 41(3), 475–512.
- Chong, Y Y and D F Hendry (1986), “Econometric evaluation of linear macro-economic models,” *Review of Economic Studies*, 53(4), 671–90.
- Clarida, R, J Gali, and M Gertler (1999), “The science of monetary policy: A new Keynesian perspective,” *Journal of Economic Literature*, 37(4), 1661–1707.
- Clark, T E and M W McCracken (2001), “Tests of equal forecast accuracy and encompassing for nested models,” *Journal of Econometrics*, 105(1), 85–110.
- Clark, T E and M W McCracken (2005), “The predictive content of the output gap for inflation: Resolving the in-sample and out-of-sample evidence,” *Journal of Money, Credit and Banking*, forthcoming.
- Clark, T E and K D West (2005a), “Approximately normal tests for equal predictive accuracy in nested models,” *Manuscript*.
- Clark, T E and K D West (2005b), “Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis,” *Journal of Econometrics*, forthcoming.
- Conway, P and B Hunt (1997), “Estimating potential output – a semi-structural approach,” *Reserve Bank of New Zealand Discussion Paper*, 1997/09.
- De Gregorio, J, A Giovannini, and H C Wolf (1994), “International evidence on tradables and nontradables inflation,” *European Economic Review*, 38(6), 1225–40.
- Devereux, M B, P R Lane, and J Xu (2005), “Exchange rates and monetary policy in emerging market economies,” *Economic Journal*, forthcoming.
- Diebold, F X and R S Mariano (1995), “Comparing predictive accuracy,” *Journal of Business and Economic Statistics*, 13(3), 253–63.
- Engel, J (1999), “Accounting for U.S. real exchange rate changes,” *Journal of Political Economy*, 3(107), 507–38.
- Gali, J and T Monacelli (2005), “Monetary policy and exchange rate volatility in a small open economy,” *Review of Economic Studies*, forthcoming.
- Grunfeld, Y and Z Griliches (1960), “Is aggregation necessarily bad?” *Review of Economics and Statistics*, 42(1), 1–13.
- Guender, A V (2005), “Stabilising properties of discretionary monetary policies in a small open economy: Domestic vs CPI inflation targets,” *Economic Journal*, forthcoming.
- Hubrich, K (2005), “Forecasting euro area inflation: does aggregating fore-

- casts by HICP component improve accuracy?" *International Journal of Forecasting*, 21(1), 119–136.
- Laxton, D and P Pesenti (2003), "Monetary rules for small, open, emerging economies," *Journal of Monetary Economics*, 50(5), 1109–1146.
- Marcellino, M, J H Stock, and M W Watson (2003), "Macroeconomic forecasting in the euro area: Country specific versus area-wide information," *European Economic Review*, 47(1), 1–18.
- Marcellino, M, J H Stock, and M W Watson (2005), "A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series," *Journal of Econometrics*, forthcoming.
- Monacelli, T (2005), "Monetary policy in a low pass-through environment," *Journal of Money, Credit and Banking*, forthcoming.
- Newey, W K and K West (1987), "A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703–708.
- Orphanides, A and S van Norden (2005), "The reliability of inflation forecasts based on output gap estimates in real time," *Journal of Money, Credit and Banking*, 37(3), 583–560.
- Robinson, T, A Stone, and M van Zyl (2003), "The real-time forecasting performance of Phillips curves," *Reserve Bank of Australia, Discussion Paper*, 2003-12.
- Stock, J H and M W Watson (1999), "Forecasting inflation," *Journal of Monetary Economics*, 44(2), 293–335.
- Stock, J H and M W Watson (2002), "Macroeconomic forecasting using diffusion indexes," *Journal of Business and Economic Statistics*, 20(2), 147–62.
- Stock, J H and M W Watson (2003), "Forecasting output and inflation: The role of asset prices," *Journal of Economic Literature*, 41(3), 788–829.
- Svensson, L E O (2000), "Open-economy inflation targeting," *Journal of International Economics*, 50(1), 155–83.
- Theil, H (1954), *Linear aggregation of economic relations*, North Holland, Amsterdam.
- West, K D (1996), "Asymptotic inference about predictive ability," *Econometrica*, 64(5), 1067–8.

Appendices

A Indicators in the Australian diffusion index*

National Accounts	
Total production GDP	Finance and insurance
Agriculture	Property and business services
Forestry and fishing	Government admin and defence
Agriculture, forestry and fishing	Education
Mining	Health and community services
Services to mining	Cultural and recreation services
Total mining	Personal and other services
Food, beverage and tobacco	Ownership of dwellings
Textile, clothing and footwear	Taxes less subsidies on products
Wood and paper products	
Printing, publishing and recorded media	NAB Quarterly Survey
Petroleum, coal, chemicals etc	Number of employees last 3 months
Non-metallic mineral products	Number of employees next 3 months
Metal products	Number of Employees next 12 months
Machinery and equipment	Business Conditions Last 3 months
Other manufacturing	Business Conditions Next 3 months
Total manufacturing	Business Conditions Next 12 months
Electricity	Trading Conditions Last 3 months
Gas	Trading Conditions Next 3 months
Water supply, sewerage services	Business confidence next 3 months
Electricity, gas and water	Profitability last 3 months
Construction	Profitability next 3 months
Wholesale trade	Capacity Utilisation
Retail trade	Forward orders last 3 months
Accommodation, cafes and restaurants	Forward orders next 3 months
Road	Stocks last 3 months
Air and space	Stocks next 3 months
Rail, pipeline and other transport	Premises and plant: significant
Transport services and storage	Availability of suitable labour: significant
Transport and storage services	Sales and orders: significant
Communication Services	Availability of materials: significant

* All survey data are in levels and all national accounts data are in (log) first differences before the first principal component is extracted each quarter. The national accounts data are advanced one quarter to simulate a publication lag that exists between the survey data and the national accounts data in real time.

B Indicators in the New Zealand diffusion index*

National Accounts	Finance, property and business
Total production GDP	Education, health, personal and other
Agriculture	Ownership of dwellings
Forestry, fishing, mining	General govt services (central)
Fishing and hunting	General govt services (local)
Forestry and logging	General government services
Mining and quarrying	Service Industries
Primary industries	
Primary food	NZIER – QSBO
Other food	Capacity Utilisation
Primary food, beverage, tobacco	Domestic Trading Activity last 3 months
Textile, clothing and footwear	Domestic Trading Activity next 3 months
Wood and paper products	Difficulty finding labour: skilled
Printing, publishing and recorded media	Difficulty finding labour: unskilled
Petroleum, coal, chemicals etc	Business confidence
Non-metallic mineral products	Expected investment: new buildings
Metal products	Expected investment: plant and machinery
Machinery and equipment	Factor limiting prod: capital
Other manufacturing	Factor limiting prod: finished goods
Total manufacturing	Factor limiting prod: labour
Electricity, gas and water	Factor limiting prod: material
Construction	Factor limiting prod: new orders
Goods Producing industries	Factor limiting prod: other
Wholesale trade, retail trade, and rest	Number of employees last 3 months
Wholesale trade	Number of employees next 3 months
Retail trade, including motor vehicle repairs	Profitability last 3 months
Retail trade, accomm, cafes, rest	Profitability next 3 months
Accommodation, rest, cafes	Overtime worked last 3 months
Transport, comm, bus and personal services	Overtime worked next 3 months
Transport storage	
Communications	
Transport, storage and communications	
Finance and insurance	
Property and business services	

* All survey data are in levels and all national accounts data are in (log) first differences before the first principal component is extracted each quarter. The national accounts data are advanced one quarter to simulate a publication lag that exists between the survey data and the national accounts data in real time.

C RMSFEs of univariate models

h	Australia			New Zealand		
	2	4	8	2	4	8
CPI						
AR(1)	0.39	0.51	1.00	0.56	1.05	1.58
RW	0.76	1.28	2.78	0.66	1.45	3.01
RW-M	0.37	0.51	1.01	0.60	1.07	1.61
AR-AIC	0.39	0.51	1.00	0.56	1.05	1.58
AR-BIC	0.39	0.51	1.00	0.56	1.05	1.58
Non-tradable						
AR(1)	0.53	1.03	2.19	0.51	0.96	1.89
RW	0.47	0.77	1.72	0.47	1.06	2.43
RW-M	0.61	1.17	2.47	0.69	1.32	2.59
AR-AIC	0.60	1.16	2.46	0.61	1.20	2.51
AR-BIC	0.58	1.14	2.44	0.61	1.22	2.53
Tradable						
AR(1)	0.95	1.40	2.39	1.19	2.15	3.50
RW	1.30	2.08	4.59	1.15	2.23	5.22
RW-M	0.92	1.42	2.43	1.19	2.12	3.54
AR-AIC	0.95	1.43	2.52	1.10	2.02	3.64
AR-BIC	0.95	1.43	2.46	1.09	2.02	3.64

RMSFE denotes Root Mean Squared Forecast Error for cumulative growth over h periods. Benchmark model (AR(1)), random walk (RW), random walk on the sample mean (RW-M), AR model with lags ranging from 1 to 4 selected with AIC (AR-AIC), AR model with lags ranging from 1 to 4 selected with BIC (AR-BIC). All models estimated recursively in simulated real time. Out-of-sample period from 2000Q1 to 2005Q2.

D MSFEs: Aggregate Phillips curve relative to AR

Australia	$\Delta\ln(\text{twi})$			$\Delta\ln(\text{imp})$		
	h	2	4	8	2	4
$\Delta\ln(\text{gdp})$	0.93	1.00	0.94	1.00	1.07	0.97
hp1(gdp)	0.98	2.54	1.81	1.06	2.29	1.72
hp2(gdp)	0.96	1.05	1.05	1.04	1.14	1.11
$\Delta\ln(\text{emp})$	1.13	1.47	2.36	1.33	1.66	2.37
hp1(emp)	1.09	2.08	2.90	1.21	3.12	3.23
hp2(emp)	1.21	2.24	2.67	1.20	2.73	3.10
$\Delta(\text{unemp})$	1.18	3.85	1.71	1.28	4.17	1.74
hp1(unemp)	1.11	4.86	6.81	1.20	5.11	6.84
hp2(unemp)	2.55	8.22	5.93	2.65	8.44	6.05
capu	0.89**	2.83	3.33	0.97	2.53	3.89
factor	1.33	1.97	2.40	1.37	1.42	2.49
New Zealand						
$\Delta\ln(\text{gdp})$	1.57	1.42	1.89	1.18	1.86	1.52
hp1(gdp)	1.67	1.54	1.84	2.14	2.00	2.66
hp2(gdp)	1.14	1.92	2.46	1.03*	1.97	2.16
$\Delta\ln(\text{emp})$	1.55	2.30	2.04	1.65	2.86	3.95
hp1(emp)	1.38	1.61	1.77	1.49	2.12	1.30
hp2(emp)	1.54	1.58	1.44	1.27	2.05	2.05
$\Delta(\text{unemp})$	1.94	1.83	1.87	1.15	2.17	3.38
hp1(unemp)	1.31	1.53	1.61	1.38	1.80	2.43
hp2(unemp)	1.23	1.27	1.43*	1.36	1.81	1.67
capu	1.32	1.89	2.03	1.18*	2.36	2.06
factor	1.34	1.43	1.36	1.24	1.76	1.68
gap	1.30	1.78	1.84	1.22	2.18	1.73

First differences (Δ), (log) first difference ($\Delta\ln$), one-sided HP filter (hp1), two-sided HP filter (hp2). GDP (gdp), total employment (emp), the unemployment rate (unemp), capacity utilisation (capu), diffusion index (factor), real-time output gap estimate of RBNZ (gap), nominal trade weighted index (twi), import prices (imp). ** denotes significance at the 5 per cent level. * denotes significance at the 10 per cent level. The test is one-sided and bias-adjusted. The MSFE ratios displayed are not bias-adjusted. All models estimated recursively in simulated real time.

E MSFEs: Non-tradable Phillips curves relative to AR

<i>h</i>	Australia			New Zealand		
	2	4	8	2	4	8
$\Delta \ln(\text{gdp})$	1.07	1.04	0.91**	0.66**	0.54**	0.78**
hp1(gdp)	1.39	2.00	1.77	0.94	0.84**	1.08
hp2(gdp)	1.06	1.13	1.01	0.64**	0.61**	0.78**
$\Delta \ln(\text{emp})$	1.00	1.22	1.12	1.04**	0.84**	0.84**
hp1(emp)	1.17	1.50	1.28	1.05	1.13	1.03
hp2(emp)	1.07	1.08	1.15	0.77**	0.80**	0.74**
$\Delta(\text{unemp})$	1.07	1.18	1.31	0.83**	0.82*	0.98
hp1(unemp)	1.28	1.97	1.68	1.14	1.17	1.12
hp2(unemp)	1.26	1.35	1.84	0.84**	0.92*	1.00
capu	0.92*	1.05	0.97	0.64**	0.31**	0.47**
factor	1.03	0.95	0.97	0.29**	0.16**	0.26**
gap	-	-	-	0.68**	0.64**	0.84**

First differences (Δ), (log) first difference ($\Delta \ln$), one-sided HP filter (hp1), two-sided HP filter (hp2). GDP (gdp), total employment (emp), the unemployment rate (unemp), capacity utilisation (capu), diffusion index (factor), real-time output gap estimate of RBNZ (gap), nominal trade weighted index (twi), import prices (imp). ** denotes significance at the 5 per cent level. * denotes significance at the 10 per cent level. The test is one-sided and bias-adjusted. The MSFE ratios displayed are not bias-adjusted. All models estimated recursively in simulated real time.

F MSFEs: Tradable Phillips curves relative to AR

Australia	$\Delta\ln(\text{twi})$			$\Delta\ln(\text{imp})$		
	<i>h</i>	2	4	8	2	4
$\Delta\ln(\text{gdp})$	0.87**	0.91**	0.84**	0.92*	0.95*	0.91**
hp1(gdp)	0.99	1.08	0.94**	1.08	1.16	1.08
hp2(gdp)	0.93**	0.90*	0.96	0.88**	0.94*	1.04
$\Delta\ln(\text{emp})$	0.97**	1.03	1.10	1.17	1.09	1.06
hp1(emp)	1.07	1.14	1.10**	1.12	1.32	1.46
hp2(emp)	1.03*	1.04*	1.05	1.05	1.30	1.23
$\Delta(\text{unemp})$	0.76**	1.09**	0.83**	0.84**	0.93**	0.79**
hp1(unemp)	1.20	1.89	2.32	1.14*	1.67	2.29
hp2(unemp)	1.16**	2.04	2.07	1.12**	2.17	2.01
capu	1.06**	1.20	1.24	1.02**	1.28	1.70
factor	1.11**	1.48	1.16	1.26	1.31	1.59
New Zealand						
$\Delta\ln(\text{gdp})$	0.89*	0.86*	0.89*	0.83**	0.96*	0.52**
hp1(gdp)	0.89**	1.03	0.94	0.75**	1.67	0.66**
hp2(gdp)	1.23	1.56	1.29*	1.03**	2.38	1.26
$\Delta\ln(\text{emp})$	0.98*	1.02	0.84*	0.95**	1.34	0.82*
hp1(emp)	0.94*	1.06	0.81**	0.96**	1.05	0.58**
hp2(emp)	1.03	1.08	0.73*	0.84**	1.17	0.90
$\Delta(\text{unemp})$	0.92*	0.83*	0.80*	0.91**	0.86**	0.69**
hp1(unemp)	1.01*	1.31	0.93**	0.91**	1.35	0.71**
hp2(unemp)	1.01	1.34	0.92	0.95**	1.49	0.83*
capu	0.92*	1.70	0.95	0.90*	2.31	1.03*
factor	0.79**	1.04	0.93	0.67**	1.33	0.71**
gap	1.00*	1.27	0.92**	0.99**	1.27	0.97*

First differences (Δ), (log) first difference ($\Delta\ln$), one-sided HP filter (hp1), two-sided HP filter (hp2). GDP (gdp), total employment (emp), the unemployment rate (unemp), capacity utilisation (capu), diffusion index (factor), real-time output gap estimate of RBNZ (gap), nominal trade weighted index (twi), import prices (imp). ** denotes significance at the 5 per cent level. * denotes significance at the 10 per cent level. The test is one-sided and bias-adjusted. The MSFE ratios displayed are not bias-adjusted. All models estimated recursively in simulated real time.

G MSFEs: Sectoral relative to aggregate Phillips Curves

Australia	$\Delta\ln(\text{twi})$			$\Delta\ln(\text{imp})$			
	h	2	4	8	2	4	8
$\Delta\ln(\text{gdp})$		0.95	1.23 [†]	0.88 ^{††}	0.91	1.20 [†]	0.88 ^{††}
hp1(gdp)		0.97 [†]	1.12 [†]	1.09 ^{††}	1.10	1.24 [†]	1.09 ^{††}
hp2(gdp)		1.00 ^{††}	1.16 ^{††}	0.95 ^{††}	0.95 [†]	1.12 ^{††}	0.92 ^{††}
$\Delta\ln(\text{emp})$		0.89 [†]	1.15 ^{††}	0.68 ^{††}	1.03	1.05 [†]	0.62 ^{††}
hp1(emp)		1.00 ^{††}	1.26 ^{††}	0.76 ^{††}	1.06 [†]	0.90 ^{††}	0.82 ^{††}
hp2(emp)		0.89 ^{††}	0.82 ^{††}	0.81 ^{††}	0.94 ^{††}	0.82 ^{††}	0.76 ^{††}
$\Delta(\text{unemp})$		0.91 ^{††}	0.67 ^{††}	0.92 ^{††}	0.69 ^{††}	0.54 ^{††}	0.88 ^{††}
hp1(unemp)		1.74 ^{††}	1.19 ^{††}	0.83 ^{††}	1.35 ^{††}	1.02 [†]	0.80 ^{††}
hp2(unemp)		0.70 ^{††}	0.58 ^{††}	1.00 [†]	0.51 ^{††}	0.66 ^{††}	0.95 [†]
capu		0.91 [†]	0.39	0.43	0.87 [†]	0.47	0.64
factor		0.88	1.00	0.54	0.82	1.14	0.71
New Zealand							
$\Delta\ln(\text{gdp})$		0.49 ^{††}	0.70 ^{††}	0.76 ^{††}	0.76 ^{††}	0.55 ^{††}	0.63 ^{††}
hp1(gdp)		0.77 ^{††}	0.80 ^{††}	0.72 ^{††}	0.53 ^{††}	1.03 ^{††}	0.48 ^{††}
hp2(gdp)		1.06 ^{††}	0.82 [†]	0.84 ^{††}	1.00 ^{††}	1.09 ^{††}	0.92 ^{††}
$\Delta\ln(\text{emp})$		0.72 ^{††}	0.43 ^{††}	0.57 ^{††}	0.60 ^{††}	0.48 ^{††}	0.32 ^{††}
hp1(emp)		0.90 ^{††}	0.89 ^{††}	0.71 [†]	0.77 ^{††}	0.69 ^{††}	0.89 ^{††}
hp2(emp)		0.72 ^{††}	0.50 ^{††}	0.46 ^{††}	0.74 ^{††}	0.46 ^{††}	0.47 ^{††}
$\Delta(\text{unemp})$		0.39 ^{††}	0.35 ^{††}	0.53 ^{††}	0.71 ^{††}	0.37 ^{††}	0.25 ^{††}
hp1(unemp)		0.92 ^{††}	0.92 ^{††}	0.63 ^{††}	0.74 ^{††}	0.84 ^{††}	0.46 ^{††}
hp2(unemp)		0.83 ^{††}	0.70 ^{††}	0.40 ^{††}	0.73 ^{††}	0.64 ^{††}	0.39 ^{††}
capu		0.54	0.65	0.30 ^{††}	0.60 [†]	0.70 ^{††}	0.40 ^{††}
factor		0.59 ^{††}	0.65 [†]	0.73 ^{††}	0.58 ^{††}	0.69 ^{††}	0.53 ^{††}
gap		0.84 ^{††}	0.88 ^{††}	0.91 ^{††}	0.82 ^{††}	0.63 ^{††}	1.01 ^{††}

First differences (Δ), (log) first difference ($\Delta\ln$), one-sided HP filter (hp1), two-sided HP filter (hp2). GDP (gdp), total employment (emp), the unemployment rate (unemp), capacity utilisation (capu), diffusion index (factor), real-time output gap estimate of RBNZ (gap), nominal trade weighted index (twi), import prices (imp). All models are estimated recursively in simulated real-time. The MSFE ratios are displayed. ††denotes significance at the 5 per cent level. †denotes significance at the 10 per cent level. The test is a one-sided Chong and Hendry (1986) encompassing test.

H MSFEs: Sectoral Phillips curve relative to AR

Australia	$\Delta\ln(\text{twi})$			$\Delta\ln(\text{imp})$		
	h	2	4	8	2	4
$\Delta\ln(\text{gdp})$	0.88	1.23	0.83	0.91	1.28	0.85
hp1(gdp)	0.95	2.84	1.97	1.17	2.83	1.86
hp2(gdp)	0.96*	1.22	1.00	0.99**	1.27	1.02
$\Delta\ln(\text{emp})$	1.01*	1.68	1.61	1.37	1.75	1.48
hp1(emp)	1.08	2.62	2.21	1.29	2.81	2.64
hp2(emp)	1.08**	1.84	2.18	1.13*	2.24	2.36
$\Delta(\text{unemp})$	1.07**	2.60	1.56	0.88**	2.23	1.53
hp1(unemp)	1.93	5.76	5.64	1.61	5.24	5.48
hp2(unemp)	1.78*	4.78	5.93	1.36**	5.53	5.75
capu	0.81**	1.10**	1.42	0.85**	1.19*	2.50
factor	1.18**	1.97	1.29	1.13**	1.63	1.77
New Zealand						
$\Delta\ln(\text{gdp})$	0.77*	0.99	1.45	0.90*	1.02	0.96
hp1(gdp)	1.28	1.23	1.32	1.14	2.06	1.27
hp2(gdp)	1.21	1.57	2.07	1.03**	2.15	1.98
$\Delta\ln(\text{emp})$	1.12*	0.99	1.17	0.99**	1.36	1.27
hp1(emp)	1.25	1.42	1.26	1.15**	1.47	1.16
hp2(emp)	1.12	0.80*	0.66**	0.94**	0.95	0.95
$\Delta(\text{unemp})$	0.75**	0.65**	1.00**	0.83**	0.81*	0.85*
hp1(unemp)	1.20	1.40	1.02**	1.02**	1.52	1.12**
hp2(unemp)	1.02*	0.89	0.57**	0.99**	1.15	0.66*
capu	0.71**	1.23	0.61*	0.71*	1.65	0.83
factor	0.79**	0.93	0.99	0.72**	1.22	0.88
gap	1.09	1.56	1.68	1.00**	1.38	1.75

First differences (Δ), (log) first difference ($\Delta\ln$), one-sided HP filter (hp1), two-sided HP filter (hp2). GDP (gdp), total employment (emp), the unemployment rate (unemp), capacity utilisation (capu), diffusion index (factor), real-time output gap estimate of RBNZ (gap), nominal trade weighted index (twi), import prices (imp). ** denotes significance at the 5 per cent level. * denotes significance at the 10 per cent level. The test is one-sided and bias-adjusted. The MSFE ratios displayed are not bias-adjusted. All models estimated recursively in simulated real time.