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A Factor Model Analysis of the Australian Economy and Effects of Inflation Targeting

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Abstract

Based on a dynamic factor model for a dataset with more than one hundred variables, we find that macroeconomic fluctuations in Australia can be largely captured by two common factors. However, the factor structure changed soon after the introduction of inflation targeting in the 1990s, resulting in a large reduction in cross-sectional variation related to these common factors. Estimates from a block exogenous factor augmented vector autoregressive model suggest that the transmission and responsiveness of monetary policy also changed, with policy both more effective and responsive to the potential inflationary impacts of shocks following the introduction of inflation targeting.

Keywords: Inflation targeting; Monetary policy; Factor modelling; Structural change; Impulse response functions

JEL Classification: C32; C55; E31; E32; E52

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1 Introduction

The introduction of inflation targeting by the Reserve Bank Australia (RBA) in 1993 (Stevens 1999; 2003) coincided with a stabilisation of CPI inflation to an average level almost exactly at 2.5%, the midpoint of the target range of 2–3%, after having averaged around 6.5% and fluctuating dramatically in the three decades beforehand. This stabilisation is clearly evident in Figure 1, which plots CPI inflation in Australia from 1960–2017 and RBA’s target band during the inflation targeting era.

Figure 1: CPI inflation in Australia from 1960–2017

An important question is whether inflation targeting had other consequences for the Australian economy beyond stabilising the level of inflation. To address this question, we compile a large dataset of Australian macroeconomic variables and conduct factor model analysis. First, we estimate a dynamic factor model and use it to examine changes in the factor structure of the Australian economy following the introduction of inflation targeting. Second, motivated by Dungey and Pagan’s (2000) approach to modelling a small open economy, we develop a block exogenous factor augmented vector autoregressive model in order to estimate the transmission and responsiveness of monetary policy in Australia and examine how these have changed with the introduction of inflation targeting. Our focus on possible effects of inflation targeting differs from other studies that consider factor models for the Australian economy in order to track economic conditions

(Gillitzer and Kearns 2007, Gillitzer et al. 2005, Sheen et al. 2015) or forecast macroeconomic variables (Panagiotelis et al. 2019).¹

In terms of the factor structure of the Australian economy, we find that a sizeable portion of macroeconomic fluctuations in our dataset can be captured by two common factors. This result is similar to what has been found for the U.S. and other economies by Stock and Watson (2005) and many others. Although different selection criteria provide somewhat mixed signals about the exact number of common factors, recursive estimates for these criteria suggest a possible decline following the introduction of inflation targeting. This decline stands in contrast to the findings of Bai and Ng (2007) for the U.S. economy of a general increase in the estimated number of common factors over time and suggests a possible reduction in different underlying sources of macroeconomic volatility, perhaps due to an elimination of certain types of shocks hitting the economy. Our estimates for an approximate dynamic factor model with two common factors suggest that they have clear “real” and “nominal” interpretations based on their links to different types of macroeconomic variables. We then apply a test developed by Han and Inoue (2015) for a break in the factor structure and find a significant break, with test statistics for different versions of the test maximized on the same date soon after the introduction of inflation targeting in 1993.

Using our estimated dynamic factor model to look at the cross-sectional variation in the common and idiosyncratic components of macroeconomic variables before and after the introduction of inflation targeting, we find a much larger reduction in cross-sectional variation related to common factors than idiosyncratic components. In particular, inflation targeting appears not just to have stabilised the level of inflation, as suggested in Figure 1, but also to have helped stabilise common movements in macroeconomic variables. This reduction in cross-sectional variation related to common factors is broad based, applying to both real and nominal variables. Meanwhile, the fact that cross-sectional variation in idiosyncratic components has not changed by as much suggests that signal-to-noise ratios for common and idiosyncratic movements in important variables such as real GDP growth or CPI inflation have declined, making the implied benefits of using estimated factors rather than proxying for real and nominal fluctuations with noisy individual series even

¹For a comprehensive survey of factor models and their different uses in empirical macroeconomics, see Stock and Watson (2016).

greater during the inflation targeting era.²

For our block exogenous factor augmented vector autoregressive model, estimates suggest that a contractionary monetary policy shock in the form of surprise increase in the policy interest rate leads to both lower aggregate output and lower inflation, thus resolving the so-called “price puzzle” (i.e., an estimated positive response of inflation to a contractionary monetary policy shock), as Bernanke et al. (2005) were also able to do for the U.S. economy with their factor augmented vector autoregressive model.³ The accumulated response of log CPI settles at a permanently lower level, making it clear that the RBA targets inflation, not the price level (i.e., it lets “bygones be bygones”, as argued by Stevens 1999). The responses of other variables in the dataset to a monetary policy shock are generally intuitive. Meanwhile, subsample estimates suggest monetary policy has become more persistent and effective following the introduction of inflation targeting and there are larger estimated responses of the policy interest rate to the potential inflationary impacts of foreign demand and commodity price shocks.

Our findings have important implications for monetary policy. First and foremost, they suggest that the benefits of inflation targeting are more than just in terms of stabilising the level of inflation, but also appear to be in terms of reducing the common variability of macroeconomic variables. Importantly, this link in timing of a reduction in macroeconomic fluctuations with inflation targeting would be less apparent by looking only at individual series, but is quite evident from our factor model analysis. Related, because cross-sectional variation in idiosyncratic components has not reduced by as much as for common components, our results suggest benefits of measuring aggregate real activity and inflationary pressures using a factor modelling approach. The absence of a “price puzzle” for our factor augmented vector autoregressive model provides an immediate example of such a benefit. The factor modelling approach also allows for estimation of the effectiveness and responsiveness of monetary policy in a data-rich environment, as well as the possibility of relating the effects of policy to any variable in our dataset or, indeed, any variable that is correlated with the factors.

²The idea that idiosyncratic components represent noise is predicated on the notion that macroeconomic phenomena such as aggregate real activity and inflationary pressures should affect a wide set of macroeconomic variables, while movements in variables that do not have a broad impact must reflect idiosyncratic phenomena at a more disaggregated microeconomic level or measurement error.

³See Bishop and Tulip (2017) on the difficulties in resolving the price puzzle with Australian structural vector autoregressive models.

The rest of this paper is organised as follows. Section 2 describes the dataset, investigates the relevant number of common factors, presents estimates for an approximate dynamic factor model, and conducts a break test for the factor structure of the Australian economy. Section 3 examines what a change in the factor structure implies about possible effects of inflation targeting and draws some broad implications for monetary policy. Section 4 presents our block exogenous factor augmented vector autoregressive model of the Australian economy and further investigates implications of the factor structure for the transmission and responsiveness of monetary policy, including how these have changed with the introduction of inflation targeting. Section 5 concludes. Full details of the dataset and estimation methods, as well as various robustness checks, are provided in an online appendix.

2 The Factor Structure of the Australian Economy

2.1 Dataset

We expand the datasets in Gillitzer et al. (2005) and Gillitzer and Kearns (2007) to cover 104 macroeconomic variables for the Australian economy over the sample period of 1976:Q4 to 2017:Q2.⁴ Due to data availability, the broader coverage of variables necessitates a later starting point for the sample period than in Gillitzer et al. (2005) and Gillitzer and Kearns (2007). However, the sample period still includes 15 years before the introduction of inflation targeting in mid 1993 and nearly 25 years since its introduction.

Because many of the time series in our dataset appear to be nonstationary, we transform variables by taking logs and/or first differences, as appropriate. As part of these transformations, we allow for a structural break in the mean levels of all the price growth series in 1993:Q1, corresponding to the introduction of inflation targeting and motivated by the change in the mean level of CPI

⁴Gillitzer et al. (2005) and Gillitzer and Kearns (2007) focus on smaller datasets and extracting a single coincident business cycle index for the Australian economy rather than looking at the effects of inflation targeting on the Australian economy. Similarly, Sheen et al. (2015) construct a daily coincident index using mixed frequency modelling of a smaller-scale dynamic factor model. By contrast, Panagiotelis et al. (2019) consider an even larger dataset of Australian macroeconomic variables and focus on forecasting. They find that factor models perform poorly in forecasting the Australian economy, although they do not consider a possible change in the factor structure with the introduction of inflation targeting that we find in our analysis.

inflation that is evident in Figure 1. This adjustment renders all of the log price series stationary in first differences according to unit root tests and avoids needing to consider some series in second differences, which would make interpretation of the factors considerably more complicated.⁵ Once a given variable has been transformed to be stationary, we standardise the resulting time series by subtracting any remaining sample mean and dividing by the sample standard deviation. This standardisation implicitly gives each variable equal weight in fitting with a factor model.

In terms of types of variables in our dataset, about half relate to real economic activity, while most of the other variables correspond to prices or monetary and financial conditions. Table 1 provides a more detailed breakdown into categories that we will refer to when interpreting estimated common factors. The full list of the variables and their corresponding data transformations are provided in Online Appendix A.

Table 1: Number of variables by category

Category	Number
Expenditure	20
Production	19
Income	5
Employment	8
Surveys	5
Building and capex	5
Overseas transactions	5
Prices	20
Money and credit	6
Interest rates	8
Miscellaneous	3
Total	104

Note: ‘Miscellaneous’ includes Share Price Index, Real Trade Weighted Index, and the Southern Oscillation Index.

2.2 How Many Common Factors?

Figure 2 displays the scree plot for our dataset based on principal components analysis (PCA). The scree plot provides a simple diagnostic for the likely number of relevant common factors. For

⁵It is important to note that allowing for a structural break in the mean level of price growth series should not induce any spurious evidence of a structural break in the factor structure of the Australian economy. If no structural break in mean price growth were actually present, then allowing for one would have little impact on estimates of common factors. By contrast, if a structural break is present but not accounted for, it would lead to distorted estimates of common factors that could lead to spurious evidence of a structural break in the factor structure.

our dataset, the largest two eigenvalues from PCA explain much more variation than all of the remaining eigenvalues. This result is suggestive of two relevant common factors, which capture about 13% and 9%, respectively, of the joint variation in the macroeconomic variables, with the remaining “scree” corresponding to much less relevant common factors in terms of amount of variation explained or possibly even idiosyncratic movements in subsets of the variables. This finding of two dominant common factors is consistent with what has been found for macroeconomic datasets from other countries, including for U.S. data by Stock and Watson (2005).

Figure 2: Scree plot based on PCA for Australian macroeconomic variables

As can be seen from the cumulative explained variation in Figure 2, the next eight largest eigenvalues from PCA more than double the total variation explained. Thus, it is unclear whether two common factors are actually sufficient to capture common variation for our dataset. Starting with Bai and Ng (2002), a number of formal selection criteria have been developed to determine the number of relevant common factors. Table 2 reports results for these formal selection criteria, which provide somewhat mixed signals about the exact number of relevant common factors. In particular, while most of the criteria select two common factors, there could be as many as seven.

When estimating our factor model for the Australian economy below, we assume two common factors. We are motivated to do so based on the scree plot and the results of a majority of the formal selection criteria, particularly the IC_{P2} criteria of Bai and Ng (2002), which has previously been shown to have good properties in simulations (Bai and Ng 2008). Also, as we will see, two common factors appear to be sufficient to capture any persistent common variation in the dataset.

Meanwhile, evidence for more than two common factors, such as suggested by the Onatski (2010) criterion, could reflect a change in the factor structure rather than the actual relevance of more than two factors in explaining common variation in the data.

Table 2: Number of common factors

Method	Number
Bai and Ng (2002)	
PC_{P2}	4
IC_{P2}	2
Ahn and Horenstein (2013)	
ER	2
GR	2
Onatski (2010)	
ED	7

Note: The upper bound on the maximum number of factors used with each method was 10.

As a first step to looking at possible changes in the factor structure, Figure 3 plots recursive (expanding window) estimates of the number of common factors using the formal selection criteria considered in Table 2.⁶ By construction, the end-of-sample estimates are the same as reported in the table. However, what is notable about the recursive estimates is that the criteria suggesting a larger number of common factors show a marked decline in the estimated number of factors during the inflation targeting era since 1993:Q1. This decline contrasts with findings in Bai and Ng (2007) of an increase in the estimated number of factors for the U.S. economy over time. Instead, it is consistent with a particular type of change in the factor structure that is due to a reduction of distinct sources of common variation rather than a change in cross-correlations related to a fixed number of common factors. We investigate this possibility directly in Section 3.

⁶For the recursive estimates, the initial window is 20 quarters and we always consider a maximum of 10 common factors. Letting Y denote the $T \times N$ matrix of data, we calculate a covariance matrix based on YY' when $T < N$ and $Y'Y$ when $T > N$. We focus on recursive rather than rolling-window estimates because they better illustrate possible permanent changes in the factor structure, while rolling windows could capture possible recurring changes and are also sensitive to the window size. For recurring changes, this sensitivity to window size makes it preferable to formally test and model the changes via a regime-switching factor model. We leave such analysis for future research.

Figure 3: Recursive estimates of the number of common factors

2.3 An Approximate Dynamic Factor Model

Let the $N \times 1$ vector of transformed variables in our dataset at time t be denoted by y_t , where $t = 1, \dots, T$, with $T = 163$ and $N = 104$. We assume the variables in the dataset have the following factor structure:

$$y_t = \Lambda f_t + \epsilon_t, \quad (1)$$

where f_t is an $r \times 1$ vector of latent common factors, with $r = 2$ based on a majority of the formal selection criteria, and ϵ_t is an $N \times 1$ vector of idiosyncratic (series-specific) components. Λ is an $N \times r$ matrix of factor loadings that indicate how much each series in y_t relates to each factor in f_t , with initial normalisation $\Lambda' \Lambda = N I_r$ and factor orthogonality.⁷ We also assume the dynamics of the common factors can be captured by a vector autoregressive (VAR) process of order p :

$$f_t = \sum_{i=1}^p \Phi_i f_{t-i} + \eta_t \quad (2)$$

where Φ_i is an $r \times r$ matrix of VAR coefficients and η_t is an $r \times 1$ vector of serially-uncorrelated innovations. Based on the Schwarz information criterion (SIC), we set $p = 2$ in our estimation.

The model is “approximate” in the sense following Stock and Watson (2002) and Forni et al. (2000)

⁷In practice, we standardise the estimated factors for ease of interpreting their units. Thus, our final normalisation is $\mathbb{E}[f_t f_t'] = I_r$, with the sign of loadings the same as the initial normalisation.

that the elements of ϵ_t may be weakly dependent cross-sectionally and across time, although it is strictly assumed that $\mathbb{E} [\epsilon_t \eta'_{t-k}] = 0, \forall k$. The model is “dynamic” in the sense following Doz et al. (2011; 2012) that the common factors have an explicit VAR structure. Also following Doz et al. (2011; 2012), we impose cross-sectional independence of the idiosyncratic components $\mathbb{E} [\epsilon_{i,t} \epsilon'_{j,t}] = 0 \forall i \neq j$ when estimating the model. Then, to the extent the estimated model is misspecified given an actual presence of cross-sectional correlation in the idiosyncratic components, in addition to fact that some of the data may not be Normally distributed, parameter and factor estimates obtained via the Kalman filter-smoother and the Expectation-Maximisation (EM) algorithm will correspond to “quasi” maximum likelihood estimation (QMLE). Doz et al. (2012) show that the effects of misspecification on the estimation of the common factors is negligible for large sample size T and cross-sectional dimension N , which we have for our dataset. See Online Appendix B for details on the implementation of QMLE for the approximate dynamic factor model.

Figure 4: Estimated common factors and 95% confidence intervals

Figure 4 plots the QMLE-based estimates of the two dynamic factors for our dataset.⁸ In addition, we report the 95% confidence interval for each factor based on the Kalman filter-smoother. Being able to report confidence intervals for the dynamic factors is one of the benefits of using the QMLE approach compared to PCA. Notably, the confidence intervals for both factors are relatively tight, suggesting they are well identified in the dataset. Both factors display considerable persistence, with fewer extreme realisations (e.g., more than two standard deviations) since the mid 1990s.

⁸For ease of interpretation as a real activity factor, we renormalise the sign of the first factor from the initial PCA estimate such that real GDP growth has a positive loading.

Figure 5: Average R^2 statistics by variable category given orthogonal factors

Figure 5 reports on the fractions of variances explained by the common factors based on average R^2 statistics by variable category given orthogonal common factors. The fact that these fractions are all reasonably low suggests that many of the variables in each category are subject to considerable idiosyncratic variation.⁹ It is also clear from these results that the first dynamic factor relates to “real” variables such as measures of activity surveys, employment, and expenditure, while the second dynamic factor relates to “nominal” variables, such as prices, money, credit, and interest rates. Notably, we find that interest rate spreads in particular load on both common factors, which likely reflects their information content for both real activity and inflationary pressures.

2.4 Has the Factor Structure Changed?

As noted above, one reason why some formal selection criteria might suggest more than two factors could be that there has been a change in the factor structure. We formally test for a change in the factor structure using an approach recently proposed by Han and Inoue (2015).¹⁰ The formal null

⁹Notably, when we estimated a third dynamic factor, we found that it was not persistent at all and explained very little variation across all categories. Thus, consistent with the scree plot and most of the formal selection criteria discussed previously, it appears that two common factors are, indeed, sufficient to capture any sizeable persistent common variation in our dataset.

¹⁰Breitung and Eickmeier (2011) and Chen et al. (2014) also develop tests for instability in factor models. However, both of these alternative tests have drawbacks. For example, Breitung and Eickmeier’s (2011) joint test

hypothesis for their test is that all factor loadings are constant over time versus the alternative that a non-negligible fraction of factor loadings have changed. The test makes use of the fact that the presence of a structural break in factor loadings implies changes in the second moments of the factors. Importantly, however, Han and Inoue (2015) note that a change in the volatility of factors or in factor loadings are not actually separately identified, so a rejection of their test could reflect either or both. The idea of a change in factor loadings for their test being related to the emergence of additional underlying common sources of variation corresponds to what Han and Inoue (2015) call a “Type 1” break, where the change in the factor structure ultimately reflects a change in cross-correlations between variables related to common factors (i.e., a change in loadings given a particular set of estimated factors). By contrast, the idea of a change in factor loadings for their test being related to a change in the volatility of factors corresponds to what Han and Inoue (2015) call a “Type 2” break, where the change in the factor structure ultimately reflects a change in the volatility of variables related to common factors, but with stable cross-correlations between variables related to the common factors (i.e., stable loadings given a particular set of estimated factors). Our earlier finding of a reduction in the estimated number of factors for some of the criteria in Figure 3 is more consistent with a “Type 2” break than a “Type 1” break, but we will examine issue this directly in the next section.

Figure 6 plots the Han and Inoue (2015) Wald and LM test statistics for a break in the factor structure. In both cases, the test statistic is maximised in 1994:Q3 (denoted by the solid vertical line), although only the Wald test is significant at the 5% level, while the LM test is just shy of the 5% critical value, but would clearly be significant at a 10% level. Notably, this date is close to the introduction of inflation targeting in 1993:Q2 (denoted by the dashed vertical line).¹¹ Thus, the results for Han and Inoue’s (2015) test are consistent with the idea that the introduction of inflation targeting altered the factor structure of the Australian economy.¹²

appears to be oversized when idiosyncratic errors contain serial correlation and a HAC-based covariance matrix estimator is used. Meanwhile, the LM version of Chen et al.’s (2014) test is not consistent in some settings. Importantly, Monte Carlo analysis in Han and Inoue (2015) suggests that their test has better finite-sample performance compared to Chen et al. (2014).

¹¹The timing of a break in 1994 is notable as fast wage growth led the RBA to aggressively raise rates by 275 basis points in the second half of the year. Thus, this tightening episode was the first major test of the credibility of what was then a nascent inflation targeting regime and it had large effects on the real economy and keeping inflation in check. As a result, the last quarter of 1994 may be the logical timing for the inflation targeting regime to have had a broader impact on the economy rather than just after its launch in 1993. We thank a referee for pointing out this important detail regarding the timing to us.

¹²Han and Inoue’s (2015) test only considers whether there is a change in the factor structure rather than

Figure 6: Test statistics for a break in the factor structure

3 Implications of the Factor Structure for Possible Effects of Inflation Targeting

3.1 Less Cross-Sectional Variation Due to Common Shocks

Beyond the stabilisation of the level of CPI inflation evident in Figure 1, are there other possible effects of the introduction of inflation targeting in Australia? The estimated timing of a change in the factor structure of the Australian economy in the previous section directly implies that there are. In particular, factor models are designed to explain the common sources of variation in different time series rather than changes in mean. Along these lines, we find using the approximate dynamic factor model from the previous section that the introduction of inflation targeting corresponded to a much larger reduction in the variation associated with common components of macroeconomic time series than with their idiosyncratic components.

providing a sequential test for multiple possible breaks. We do not know of a sequential test in the context of factor models. Thus, we focus on the estimated break for this test given its close proximity to the introduction of inflation targeting and leave analysis of possible additional breaks to future research. Also, as noted to us by a referee, Han and Inoue's (2015) test was originally designed to be used with PCA estimates, while we use QMLE-based estimates. To address this, we checked the robustness of our results when applying the test to factors estimated using PCA. The results are robust in terms of the significance of the tests and the profiles of test statistics across break dates are reasonably similar, although the date at which the test statistic is maximized occurs somewhat later for the Wald test, while it is identical to the QMLE case for the LM test. The results for this robustness check and a comparison of the QMLE and PCA estimated factors are reported in Figures A1 and A2 in Online Appendix C.

Figure 7: Realised measures of common and idiosyncratic volatility

To examine these changes in sources of variation in macroeconomic variables, we calculate the cross-sectional standard deviation of common components and idiosyncratic components implied by the approximate dynamic factor model at each point of time.¹³ Figure 7 plots these realised measures of common and idiosyncratic volatility over the whole sample period for i) all of the variables, ii) only real variables, iii) only nominal variables, and iv) only price variables. The pattern is consistent in all of the cases. Although there are still peaks in both realised measures of volatility after the introduction of inflation targeting that seem to be related to events such as the introduction of the goods and services tax in 2000 (idiosyncratic volatility) and the global financial crisis in 2007–2009 (both common and idiosyncratic volatility), there appears to be lower common volatility on average since the introduction of inflation targeting. The absence of a recession in Australia since the early 1990s could explain some of a relative lack of peaks in common volatility that occurred with the recessions in the early 1980s and 1990s. However, even abstracting from such peaks, common volatility is generally lower after the introduction of inflation targeting than it was during expansions prior to the start of inflation targeting. Furthermore, contrary to recessions being the primary driver of cross-sectional variation, idiosyncratic volatility is generally much

¹³We report results based on full-sample estimates, which Bates et al. (2013) and Stock and Watson (2009) suggest remain consistent even if there is a large discrete break in factor loadings. We do so because having fixed loadings across the whole sample period keeps the interpretation of the estimated factors straightforward. However, as shown in Figure A3 in Online Appendix C, the results for cross-sectional standard deviations are robust to separate estimation of the dynamic factor model for pre and post break sample periods.

higher than common volatility and only looks slightly lower on average since the introduction of inflation targeting (and possibly not even so for prices).

Because the reduction of idiosyncratic volatility is not as large as for common volatility, implied signal-to-noise ratios for individual variables proxying for the common factors must have declined since the introduction of inflation targeting. Figure 8 illustrates this decline in signal-to-noise ratios by plotting the common and idiosyncratic components of (adjusted and standardised) real GDP growth and CPI inflation. The variation in both components for each series appears to have declined somewhat with the introduction of inflation targeting, but more so for the common components, especially in the case of CPI inflation.¹⁴ Thus, a higher proportion of the quarterly fluctuations in CPI inflation would seem to reflect noise rather than a persistent change in underlying inflationary pressures since the introduction of inflation targeting. In particular, the lack of persistence of the idiosyncratic component of CPI inflation supports this interpretation of noise that the RBA can “look through” when tracking inflationary pressures.¹⁵

Figure 8: Common and idiosyncratic components of real GDP growth and CPI inflation

¹⁴Comparing before and after 1993:Q2, the sample standard deviations of the common and idiosyncratic components of real GDP growth fell from 0.91 to 0.51 and 0.83 to 0.52, respectively, while the sample standard deviations of the common and idiosyncratic components of CPI inflation fell from 0.89 to 0.42 and 0.89 to 0.60, respectively.

¹⁵We cannot reject the null of no serial correlation in the idiosyncratic component of CPI inflation for a Ljung-Box Q -test based on four lags.

3.2 Stabilised Factor Loadings

To further investigate the implications of the factor structure of the Australian economy for the effects of inflation targeting, we calculate recursive estimates of factor loadings for real GDP growth, CPI inflation, and the RBA’s policy interest rate (the Overnight Cash Rate, hereafter OCR) on the two estimated common factors from the previous section. Figure 9 plots these recursive estimates along with 95% confidence bands based on inverted t tests using the alternative HAC standard errors proposed in Hartigan (2018). Real GDP growth and the OCR load significantly on both factors, while CPI inflation only loads significantly on the second factor. The estimated loadings for all three variables on the first factor are positive (although, again, insignificant for CPI inflation). This suggests the first factor could reflect demand pressures in the economy. The estimated loadings for the second factor are negative on real GDP growth and positive for CPI inflation and the OCR, suggesting it could reflect supply-side inflationary pressures.

Notably, the recursive estimates of the factor loadings seem to stabilise rather than suddenly jump following the introduction of inflation targeting. This is consistent with a “Type 2” break in Han and Inoue (2015) for which the break in factor structure reflects a change in the volatility related to common factors rather than a change in cross-correlations related to common factors under a “Type 1” break, which would have corresponded to a shift in estimated factor loadings on a given set of estimated factors or, equivalently, an increase the recursive estimates of the number of common factors in Figure 3. Thus, according to these results, inflation targeting again appears to have corresponded to a reduction in overall macroeconomic volatility.

Figure 9: Recursive estimates of factor loadings

3.3 Broad Implications

The change in the factor structure of the Australian economy suggests that inflation targeting has done more than just stabilise the level of inflation in Australia. It also appears to have helped reduce the volatility of common movements in macroeconomic variables and, looking back to Figure 3, possibly even reduced the number of distinct sources of variation in the economy. This decline in volatility is not just in inflation and other nominal variables, but is broad based and could be driven by an elimination of “sunspot” shocks following the introduction of inflation targeting due to its provision of a clear nominal anchor for inflation expectations.¹⁶ Meanwhile, the estimated timing of the reduction in macroeconomic volatility that is linked to the introduction of inflation targeting is also different than an estimate in the mid 1980s corresponding to the so-called “Great Moderation” that, based on the noisier real GDP growth and CPI inflation series, had been found by others to have occurred in Australia around the same time as in the United States and argued to have reflected global forces (e.g., Summers 2005).¹⁷

¹⁶See Lubik and Schorfheide (2004) and Lubik and Surico (2010) on the interaction between monetary policy and sunspot shocks.

¹⁷Also see Cecchetti et al. (2005) and the discussion of it by Dungey (2005) for evidence of a structural break in the volatility of Australian real GDP growth in the mid 1980s and further consideration of the extent to which it might reflect global forces.

The larger drop in the volatility of common components relative to idiosyncratic components also implies an increased benefit of looking at common factors to eliminate possible noise in individual series. Notably, price measures, including the RBA’s numerical target variable CPI inflation, have particularly large idiosyncratic components, while the factor model estimates suggests that the RBA can “look through” most quarterly fluctuations in these measures given their lack of persistence and focus on the more persistent common component of price growth variables provided by the approximate dynamic factor model. Perhaps ironically then, the apparent success of inflation targeting in reducing macroeconomic volatility has also reduced the relative accuracy of the RBA’s target variable of CPI inflation in providing signals about underlying inflationary pressures in the Australian economy.¹⁸

Meanwhile, the stabilised factor loading estimates directly imply that, despite a change in the factor structure, a factor-augmented vector autoregressive (FAVAR) model with two estimated factors should also have stable factor loadings. We consider such a model to examine the transmission and responsiveness of monetary policy for the Australian economy in the next section.

4 Further Implications of the Factor Structure for the Transmission and Responsiveness of Monetary Policy

4.1 A Block Exogenous FAVAR Model with Two Unobserved Factors

Building on Bernanke et al. (2005, BBE hereafter), we estimate a FAVAR model based on their preferred specification of using the (domestic) policy interest rate as an observed (domestic) factor, but supplemented with a block of exogenous foreign variables, as often considered in VARs for small open economies such as Australia (see Dungey and Pagan 2000; 2009). Following the standard nomenclature for block-exogenous VARs, we label this as a “FAVARX” model.

Our FAVARX model has factor loadings which relate the full dataset to an underlying eight-

¹⁸See Gillitzer and Simon (2015) on the implications of inflation targeting for the relevance of CPI inflation as a measure of inflationary pressures in Australia. They also document that financial-market inflation expectations have become better anchored in Australia since the introduction of inflation targeting.

variable VAR that includes the RBA index of commodity prices (ICP), U.S. real GDP growth, U.S. CPI inflation, the U.S. Federal Reserve’s policy interest rate (the Federal Funds Rate, FFR), two unobserved common factors corresponding to “real” and “nominal” fluctuations from our Australian macroeconomic dataset, Australia’s OCR policy interest rate, and Australia’s real trade-weighted exchange rate (real TWI).¹⁹ We use the U.S. variables to proxy for global output, inflation, and monetary policy, respectively, and, following Dungey and Pagan (2000; 2009), impose block exogeneity restrictions for these variables such that domestic variables do not impact the foreign variables in the VAR.²⁰

Following Bai and Ng (2013) and Stock and Watson (2016) we estimate the two unobserved common factors using a “named-factor” normalisation for the FAVARX.²¹ This approach restricts the first factor loading on the first variable in the dataset to be 1 and the second factor loading on the second variable in our dataset to be 1. Given the previous findings about the first factor being a “real” factor and the second factor being a “nominal” factor, we set the first variable to be real GDP growth and the second variable to be CPI inflation. We note that the named-factor normalisation identifies the sign and scale of the factors to be the same as the naming variables.²²

Similar to BBE, we extract the unobserved factors from the subset of “slow-moving” variables (i.e., we exclude, for example, survey measures, oil prices, commodity prices, financial variables, and the exchange rate – the full list is given in the dataset table in Online Appendix A). Crucially, this subset excludes the OCR and the factors are then “rotated”, as in BBE, to remove any residual effects of either the foreign variables or the domestic policy interest rate. Despite these changes, the

¹⁹U.S. data are sourced from FRED and transformed to be comparable to the respective Australian variables. Meanwhile, the ICP and real TWI variables are sourced from the RBA and included in the model after transforming to log differences. The real TWI series is treated to remove three outliers in 1985:Q2, 1986:Q3, and 2008:Q4. The first two were identified by Dungey and Pagan (2000) and related to a large movement in the cash rate and the infamous “Banana republic” comment by the then Treasurer Paul Keating, respectively. The last one corresponds to the Global Financial Crisis. Each outlier is replaced by the median of the previous five observations.

²⁰Because of data availability, especially for China, we do not use trade-weighted series in these cases. This is a limitation given China’s growing role in the global economy and increasing importance to Australia in particular. However, to the extent that commodity prices are driven by global economic conditions, the role of China is implicitly accounted for via the commodity price series, as argued in Kamber and Wong (2018). Our consideration of real TWI also serves to implicitly account for more than just a U.S. based foreign sector, which Dungey and Fry (2003) find is important in the context of Australian SVARs.

²¹We thank a referee for making us aware of potential issues with using the original QMLE factors from Section 2 in a FAVAR model.

²²See Online Appendix B for more details about how we implement this normalisation and Figure A4 in Online Appendix C for a comparison of the original QMLE factors and the named factors, which are very similar in practice.

extracted factors end up looking very similar to common factors estimated from the full dataset, as can be seen in Figure 10.²³ Then, monetary policy shocks are identified by assuming that they are contemporaneously uncorrelated with the unobserved factors.²⁴ Following Dungey and Pagan (2000; 2009), foreign shocks are identified by the assumption of block exogeneity and recursive ordering within the block, with commodity prices ordered first and U.S. real GDP growth ordered second (followed by U.S. CPI inflation and then the FFR). Factor loadings for each series in the dataset are estimated based on the rotated unobserved and observed factors. See Online Appendix B for full details on how we estimate the FAVARX model.

Figure 10: Original factors vs. rotated factors for the “slow-moving” subset of variables

4.2 Full-Sample Estimates for Effects of Monetary Policy

Before focusing on how the effects of monetary policy have changed with the introduction of inflation targeting in the next subsection, we first consider full-sample estimates in order to provide

²³Ouliars et al. (2018) argue that the BBE approach leaves measurement error in the rotated factors that would lead to inconsistent estimates of impulse response functions and propose extracting factors using the slow-moving variables only. When we do so, we find that the second factor is almost identical as for the full dataset, but the first estimated factor is less persistent and somewhat noisier. Impulse response functions are qualitatively similar to what is presented below using BBE’s approach, although they are less economically and statistically significant, possibly due to attenuation bias from a less precise measurement of the first factor. See Figures A5-A7 in Online Appendix C for these additional results.

²⁴In practice, this identification involves ordering the OCR second to last in the VAR (before the real TWI) and using a Cholesky factorization of the forecast error variance-covariance matrix to identify monetary policy shocks. However, due to the consideration of the rotated factors based on slow-moving variables, the correlation between the forecast errors from the VAR are very low, so any particular ordering has very little effect on the identified shocks.

a benchmark for comparison. To do so, we estimate a FAVARX with one lag based on SIC for the sample period of 1980:Q1–2017:Q2 and report estimated impulse response functions for an unanticipated 25 basis points (bps) increase in the OCR, with reported 95% confidence bands based on Kilian (1998) with 1,000 bootstrap replications.²⁵ The lower lag order of the FAVARX model versus the approximate dynamic factor model in Section 2 is consistent with the incorporation of additional information in terms of foreign variables in the FAVARX model. The somewhat later start to the sample period compared to Section 2 follows Dungey and Pagan (2000), who note that the exchange rate only shifted to a more flexible regime for Australia in the late 1970s.

Figure 11 plots the estimated response to a monetary policy shock for the OCR and growth in the real TWI, as well as the implied responses for real GDP growth and CPI inflation on estimated factor loadings. By construction, the OCR increases by 25bps on impact, after which it gradually reverts back to its pre-shock level. Real GDP growth and CPI inflation both contract over business cycle horizons, while the real TWI appreciates at shorter horizons. The impact on CPI inflation is statistically significant at 1-4 year horizons, while the other responses are less precisely estimated. Overall, though, these results are consistent with the interpretation of the identified change in monetary policy as being “contractionary” in terms of having a negative liquidity effect that raises the policy interest rate, lowers aggregate output and inflation, and results in an appreciation of the exchange rate.

Accumulated responses are also reported Figure 11 in order to show the implied effects of a monetary policy shock on the log levels of real GDP, CPI and the real TWI. Consistent with monetary neutrality, there is no significant long-run effect of the monetary policy shock on log real GDP.²⁶ Meanwhile, log CPI is permanently lower following the contractionary monetary policy shock. This reflects the dynamics of the OCR in response to the policy shock, with the RBA

²⁵Kilian’s (1998) procedure involves two bootstraps. The first is designed to correct for possible bias in the parameter estimates of the VAR model. The second is used to calculate the empirical distribution of the impulse responses using the bias adjustment from the previous bootstrap. In both cases, we use 1,000 replications, as recommended by Kilian.

²⁶We check the robustness of our results to consideration of a FAVARX model with an output gap measure based on Kamber et al. (2018) instead of output growth. This model can be used to make inferences about the effects of monetary policy shocks under the assumption that the long-run effect on output is exactly zero. The responses of the OCR and CPI inflation are very similar to our benchmark case using output growth. The response of the output gap is significantly negative at business cycle horizons, but there is also an estimated depreciation of the real TWI, although it is not significant. The results for this alternative specification are given in Figure A8 in Online Appendix C.

gradually returning the policy interest rate back to its original level rather than overshooting in order to reverse the initial effects of the shock on the price level. That is, the estimated responses are consistent with the RBA targeting the inflation rate, not the price level, by letting “bygones be bygones” (Stevens 1999). The effect on log real TWI is small and not statistically significant.

Figure 11: Responses to a monetary policy shock for the FAVARX model

The impulse response function for CPI inflation in Figure 11 largely resolves the so-called “price puzzle”, just as BBE were able to do with their FAVAR model of the U.S. economy.²⁷ This finding is contrasted with Figure 12 which plots the estimated responses to a monetary policy shock for the OCR, real GDP growth, CPI inflation and growth in the real TWI based on a block-exogenous structural VAR (SVARX) model. The SVARX model is exactly the same specification as the FAVARX model except that we replace the first unobserved factor with real GDP growth and the second unobserved factor with CPI inflation. The price puzzle is quite evident in the SVARX case, with a positive response of inflation to a contractionary monetary policy shock (in terms of the responses of the OCR and real GDP growth) at all horizons. Also, the estimated response of

²⁷As noted in the introduction, the “price puzzle” is the tendency for impulse response functions to show an estimated positive effect on inflation following an identified contractionary monetary policy shock. It is often seen as a failure to completely identify the true monetary policy shock, with estimated responses partially reflecting the endogenous response of the policy interest rate to other shocks, although it could reflect a genuine economic response in the case where inflation expectations are not well anchored (see Lubik and Schorfheide 2003).

real GDP growth to a 25bps shock is much smaller than for our FAVARX model. Furthermore, there is an “exchange rate” puzzle in the sense of a depreciation in the real TWI following the contractionary monetary policy shock, although it is not statistically significant. Thus, it seems monetary policy shocks are not very well identified with the SVARX model, while they are better identified with the FAVARX model.²⁸

Figure 12: Responses to a monetary policy shock for the SVARX model

Another benefit of the FAVARX model is that it allows us to examine the effects of a monetary policy shock on any variable in the dataset (or even variables not in the dataset due to limited data availability, as long as we can determine relevant loadings on the factors). Figure 13 plots the estimated responses for a selection of variables that reflect different aspects of the Australian economy. The variables are household final consumption expenditure (Household FCE), the GDP price deflator, private-sector housing approvals, private gross fixed capital formation (Private GFCF), the domestic final demand (DFD) deflator, total credit, the unemployment rate, established house prices, and average weekly earnings. The series have been transformed to be stationary where ap-

²⁸Again, see Bishop and Tulip (2017) for full details on the difficulties in resolving the price puzzle with Australian SVARs. The impulse response functions for our FAVARX model are more similar to those for the larger 11-variable SVARX model in Dungey and Pagan (2000). The point then is that a FAVARX approach provides a way to account for relevant information, while keeping the dimension of the VAR relatively small. Boivin et al. (2010) make the same point in the context of Canadian SVARs, which also typically suffer from the price and exchange rate puzzles due to omitted information that can be handled by a FAVAR approach.

appropriate and as noted in the figure. The impulse responses behave as would be expected given a contractionary monetary policy shock. For example, there are declines in household consumption and investment, while GDP price deflator inflation and DFD price deflator inflation both behave very similarly to CPI inflation in Figure 11. The unemployment rate increases significantly at business cycle horizons and total credit growth falls significantly at business cycle horizons.

Figure 13: Responses of other variables to a monetary policy shock for the FAVARX model

4.3 Changes in the Transmission of Monetary Policy with Inflation Targeting

Motivated by the apparent change in the factor structure of the Australian economy around the introduction of inflation targeting discussed in Section 2, we re-estimate the FAVARX model for two subsample periods corresponding to before inflation targeting (1980:Q1–1993:Q1) and after the introduction of inflation targeting (1993:Q2–2017:Q2), again with one lag based on SIC in both cases.²⁹ We note that a change in the volatility of either of the two common factors could result in changes in the slope coefficients or cross-correlations of the forecast errors from the

²⁹When estimating the FAVARX model for the two subsamples, we continue to use the common factors estimated from the full sample in order to keep the interpretation of the factors the same across the subsamples. We also estimated the FAVARX for subsamples based on the break date of 1994:Q3, as determined by the Han and Inoue (2015) structural break test, and found the results were very robust compared to those reported here using the introduction of inflation targeting as the break date.

FAVARX model. In either case, it could lead to different impulse response functions compared to the full-sample results.³⁰

The effects of a contractionary monetary policy shock on the OCR, real GDP growth, CPI inflation, and growth in the real TWI for these two subsample periods are reported in Figure 14. The first column corresponds to pre inflation targeting (i.e. ‘Pre’), while the second column corresponds to post inflation targeting (i.e. ‘Post’). The figure indicates that the dynamics of a monetary policy shock changed considerably across the two subsample periods. In the pre inflation targeting period, the RBA appeared to quickly return the OCR back to its previous level following a 25bps shock. This led to less of a decline in output growth and inflation compared to the post inflation targeting period when the RBA kept the OCR elevated for longer following the initial shock. Thus, monetary policy appears to have become more persistent and its effects amplified following the introduction of inflation targeting.

Figure 14: Responses to monetary policy shocks for the FAVARX model pre and post inflation targeting

³⁰We do not formally test for differences in the impulse response functions and we acknowledge that wide confidence intervals can make it unclear whether differences in point estimates are actually statistically significant. However, some of the more precise estimates (e.g., those for the dynamics of the OCR following a monetary policy shock) do appear to be significantly different across subsample periods.

4.4 Changes in the Responsiveness of Monetary Policy to Foreign Shocks with Inflation Targeting

We can also use our FAVARX model to investigate the effects of foreign shocks on the Australian economy, including changes in how monetary policy responds to the shocks with the introduction of inflation targeting. We consider two types of foreign shocks: a foreign demand shock as proxied by a one standard deviation shock to U.S. real GDP growth and a one standard deviation shock to commodity prices as measured by the RBA index of commodity prices.

We expect a positive shock to foreign demand to have a positive effect on real GDP growth and the real TWI due to an increase in net exports. The increased demand should then flow through to higher CPI inflation and lead the RBA to raise the OCR. The expected impact of a positive shock to commodity prices on the Australian economy is more ambiguous. If it is due to an increase in global demand, then the effects will be comparable to those of the foreign demand shock. However, because we have separately identified a foreign demand shock, the increase in commodity prices could alternatively capture an adverse global supply shock along the lines of the oil price spikes in the early and late 1970s. In this case, the positive commodity price shock would be expected to have a negative effect on real GDP, but lead to a rise in CPI inflation. The effect on the real TWI is more ambiguous. Given the opposite effects on output and inflation, the reaction of the RBA is also ambiguous, but presumably would involve an increase in the OCR given sufficient weight on stabilising inflation in the RBA's objective function, at least under inflation targeting.

Figure 15 plots the the estimated responses to a foreign demand shock. The results are generally as expected, with an increase in real GDP leading to higher CPI inflation and a lifting of the OCR in both subsample periods. The real TWI appreciates in the first subsample, although it barely responds in the second subsample. Notably, as can be seen comparing the second column to the first column, the RBA's increase in the OCR is slightly larger and more persistent after the introduction of inflation targeting and the effects of the foreign demand shock on domestic output and especially inflation are somewhat muted.

Figure 15: Responses to foreign demand shocks for the FAVARX model pre and post inflation targeting

Figure 16 plots the estimated responses to a commodity price shock. The opposite effects on output and inflation in this case suggest that the shock acts more like an adverse global supply shock than a global demand shock. The real TWI initially depreciates, which also argues against interpreting the shock as being related to global demand. Meanwhile, unlike with the global demand shock, the RBA's increase in the OCR is a bit smaller and less persistent after the introduction of inflation targeting and the effect of the shock on inflation is muted. However, the differences in the RBA's reaction and the response of domestic output across the subsamples are not particularly large in this case, so it is possible that the muted response of inflation also reflects an anchoring of inflation expectations with the introduction of inflation targeting.

Figure 16: Responses to commodity price shocks for the FAVARX model pre and post inflation targeting

In summary, these results indicate that the Australia economy has become less sensitive to foreign shocks after the introduction of inflation targeting, with the RBA adjusting the policy interest rate more in response to possible inflationary effects of these shocks.

5 Conclusion

Factor model analysis provides a powerful lens through which to empirically investigate the effects of inflation targeting on the Australian economy in a data-rich environment. Notably, we find that inflation targeting not only stabilised the level of inflation, but it also appeared to help reduce macroeconomic volatility more generally. The implied decrease in signal-to-noise ratios for individual macroeconomic variables given a larger decline in variation due to common factors relative to idiosyncratic components suggests an increased benefit of tracking common factors instead of focusing only on noisy individual series such as real GDP growth and CPI inflation. Meanwhile, estimates for a block exogenous factor-augmented vector autoregressive model suggest that monetary policy shocks have become more persistent and their effects amplified following the

introduction of inflation targeting. When considering foreign shocks, our estimates suggest that their impact on aggregate output and inflation has decreased, with the RBA reaction to such shocks being larger and more persistent during the inflation targeting era.

The flexibility of factor models opens up the possibility of considering a number of extensions to our analysis. We plan in future research to estimate alternative models of structural change such as a Markov-switching dynamic factor model (Chauvet 1998, Diebold and Rudebusch 1996, Kim and Nelson 1998, and Camacho et al. 2015) or a time-varying parameter dynamic factor model (Korobilis 2013). These alternative models would let us determine if there is any recurring nonlinearities in the effects of monetary policy shocks or foreign shocks related to business cycle regimes or if there are other slower moving changes. We also plan to utilise recently developed methods for jointly estimating level and volatility factors and their interaction (e.g., Gorodnichenko and Ng 2017, Koopman et al. 2018) to empirically investigate the role of financial market volatility in driving Australian economic conditions.

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Online Appendix for “A Factor Model Analysis of the Australian Economy and the Effects of Inflation Targeting”^{*}

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^{*}The views expressed in this paper are those of the authors and should not be attributed to the Reserve Bank of Australia.

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A Dataset of Australian Macroeconomic Variables

Table A1: Full list of variables

Name	Category	Transformation	Slow Variable
Gross Domestic Product (GDP)	Expenditure	$\Delta \log(x_t)$	Yes
Non-farm GDP	Expenditure	$\Delta \log(x_t)$	Yes
GDP Per Capita	Expenditure	$\Delta \log(x_t)$	Yes
Gross Domestic Income	Income	$\Delta \log(x_t)$	Yes
Public Final Demand	Expenditure	$\Delta \log(x_t)$	Yes
Private Final Demand	Expenditure	$\Delta \log(x_t)$	Yes
Private Gross Fixed Capital Formation (GFCF)	Expenditure	$\Delta \log(x_t)$	Yes
Gross Operating Surplus: Financial Corporations	Income	$\Delta \log(x_t)$	Yes
Gross Operating Surplus: Private Non-financial	Income	$\Delta \log(x_t)$	Yes
Gross Operating Surplus: Public Non-financial	Income	$\Delta \log(x_t)$	Yes
Household Disposable Income	Income	$\Delta \log(x_t)$	Yes
Household Consumption (HC)	Expenditure	$\Delta \log(x_t)$	Yes
HC: Cigarettes and Tobacco	Expenditure	$\Delta \log(x_t)$	Yes
HC: Alcohol Beverages	Expenditure	$\Delta \log(x_t)$	Yes
HC: Clothing and Footwear	Expenditure	$\Delta \log(x_t)$	Yes
HC: Food	Expenditure	$\Delta \log(x_t)$	Yes
HC: Household Equipment	Expenditure	$\Delta \log(x_t)$	Yes
HC: Purchase of Vehicles	Expenditure	$\Delta \log(x_t)$	Yes
HC: Rent and Other Dwelling Services	Expenditure	$\Delta \log(x_t)$	Yes
HC: Hotels, Cafes and Restaurants	Expenditure	$\Delta \log(x_t)$	Yes
HC: Transport Services	Expenditure	$\Delta \log(x_t)$	Yes
Private GFCF: Dwellings: Alterations and Additions	Expenditure	$\Delta \log(x_t)$	Yes
Private GFCF: Dwellings: New and Used	Expenditure	$\Delta \log(x_t)$	Yes
Private Non-farm Inventories to Total Sales	Expenditure	Δx_t	Yes
Changes in Inventories	Expenditure	x_t	Yes
Agriculture, Forestry and Fishing	Production	$\Delta \log(x_t)$	Yes
Mining and Exploration	Production	$\Delta \log(x_t)$	Yes
Manufacturing	Production	$\Delta \log(x_t)$	Yes
Electricity, Gas and Water Services	Production	$\Delta \log(x_t)$	Yes
Construction	Production	$\Delta \log(x_t)$	Yes
Wholesale Trade	Production	$\Delta \log(x_t)$	Yes
Retail Trade	Production	$\Delta \log(x_t)$	Yes
Accommodation and Food Services	Production	$\Delta \log(x_t)$	Yes
Transportation	Production	$\Delta \log(x_t)$	Yes
Information Media and Telecommunication	Production	$\Delta \log(x_t)$	Yes
Financial and Insurance Services	Production	$\Delta \log(x_t)$	Yes
Rental, Hiring and Real Estate Services	Production	$\Delta \log(x_t)$	Yes
Professional, Scientific and Technical Services	Production	$\Delta \log(x_t)$	Yes

Continued on next page

Table A1 – continued from previous page

Name	Category	Transformation	Slow Variable
Administration and Support Services	Production	$\Delta \log(x_t)$	Yes
Public Administration and Safety	Production	$\Delta \log(x_t)$	Yes
Education and Training	Production	$\Delta \log(x_t)$	Yes
Healthcare and Social Assistance	Production	$\Delta \log(x_t)$	Yes
Arts and Recreation Services	Production	$\Delta \log(x_t)$	Yes
Other Services	Production	$\Delta \log(x_t)$	Yes
Full-time Employment	Employment	$\Delta \log(x_t)$	Yes
Part-time Employment	Employment	$\Delta \log(x_t)$	Yes
Total Employment	Employment	$\Delta \log(x_t)$	Yes
Unemployment Rate	Employment	Δx_t	Yes
Labour Productivity	Employment	$\Delta \log(x_t)$	Yes
Real Unit Labour Costs	Employment	$\Delta \log(x_t)$	Yes
Average Weekly Earnings	Employment	$\Delta \log(x_t)$	Yes
Average Weekly Hours Worked	Employment	$\Delta \log(x_t)$	Yes
Capacity Utilisation (net balance)	Surveys	x_t	No
General Business Situation (next 6 months net balance)	Surveys	x_t	No
Output Actual (change in past 3 months net balance)	Surveys	x_t	No
Output Expected (change in next 3 months net balance)	Surveys	x_t	No
Commencements: Total New Houses and Flats ex. Conversion	Building & Capex	$\Delta \log(x_t)$	No
Completed: Total New Houses and Flats ex. Conversion	Building & Capex	$\Delta \log(x_t)$	Yes
Approvals: Private New Houses and Flats	Building & Capex	$\Delta \log(x_t)$	No
Approvals: Government New Houses and Flats	Building & Capex	$\Delta \log(x_t)$	No
Approvals: Total New Houses and Flats	Building & Capex	$\Delta \log(x_t)$	No
Current Account (per cent of GDP)	Overseas Transactions	Δx_t	Yes
Services Imports	Overseas Transactions	$\Delta \log(x_t)$	Yes
Services Exports	Overseas Transactions	$\Delta \log(x_t)$	Yes
Goods Debits	Overseas Transactions	$\Delta \log(x_t)$	Yes
Goods Credits	Overseas Transactions	$\Delta \log(x_t)$	Yes
Consumer Price Index (CPI): All Groups	Prices	$\Delta \log(x_t)$	Yes
CPI: Food and Non-Alcoholic Beverages	Prices	$\Delta \log(x_t)$	Yes
CPI: Alcohol and Tobacco	Prices	$\Delta \log(x_t)$	Yes
CPI: Clothing and Footwear	Prices	$\Delta \log(x_t)$	Yes
CPI: Housing	Prices	$\Delta \log(x_t)$	Yes
CPI: Household Equipment and Services	Prices	$\Delta \log(x_t)$	Yes
CPI: Transportation	Prices	$\Delta \log(x_t)$	Yes
CPI: Communication	Prices	$\Delta \log(x_t)$	Yes
CPI: Goods Component	Prices	$\Delta \log(x_t)$	Yes
CPI: Services Component	Prices	$\Delta \log(x_t)$	Yes
Established House Prices	Prices	$\Delta \log(x_t)$	Yes
Oil Prices	Prices	$\Delta \log(x_t)$	No
GDP Price Deflator	Prices	$\Delta \log(x_t)$	Yes

Continued on next page

Table A1 – continued from previous page

Name	Category	Transformation	Slow Variable
Household Final Consumption Expenditure Price Deflator	Prices	$\Delta \log(x_t)$	Yes
Private GFCF Price Deflator	Prices	$\Delta \log(x_t)$	Yes
Domestic Final Demand (DFD) Price Deflator	Prices	$\Delta \log(x_t)$	Yes
Export Price Index: Goods and Services Credits	Prices	$\Delta \log(x_t)$	Yes
Import Price Index: Goods and Services Debits	Prices	$\Delta \log(x_t)$	Yes
Terms of Trade	Prices	$\Delta \log(x_t)$	Yes
Index of Commodity Prices (ICP)	Prices	$\Delta \log(x_t)$	No
Money: M1	Money & Credit	$\Delta \log(x_t)$	No
Money: M3	Money & Credit	$\Delta \log(x_t)$	No
Money: Broad Money	Money & Credit	$\Delta \log(x_t)$	No
Credit: Total	Money & Credit	$\Delta \log(x_t)$	No
Credit: Other Personal	Money & Credit	$\Delta \log(x_t)$	No
Credit: Business	Money & Credit	$\Delta \log(x_t)$	No
Overnight Cash Rate (OCR)	Interest Rates	Δx_t	No
Real Overnight Cash Rate	Interest Rates	Δx_t	No
3 Month Bank Bill	Interest Rates	Δx_t	No
5 Year Australia Government Security (AGS)	Interest Rates	Δx_t	No
10 Year Australia Government Security (AGS)	Interest Rates	Δx_t	No
3 Month Bank Bill spread to OCR	Interest Rates	x_t	No
5 Year AGS spread to OCR	Interest Rates	x_t	No
10 Year AGS spread to OCR	Interest Rates	x_t	No
Share Price Index	Miscellaneous	$\Delta \log(x_t)$	No
Real Trade Weighted Exchange Rate Index (TWI)	Miscellaneous	$\Delta \log(x_t)$	No
Southern Oscillation Index (SOI)	Miscellaneous	x_t	No
Consumer Sentiment Index	Surveys	x_t	No

Notes: Data are sourced from the ABS and RBA for the sample period of 1976:Q4 to 2017:Q2. When available, seasonally adjusted data are used. Monthly series are converted to quarterly by taking three-month averages. The ‘Money & Credit’ series are adjusted for changes in the number of reporting institutions and other reporting changes. ‘Slow Variable’ refers to whether the respective series is used to extract ‘slow-moving’ factors as part of the procedure when estimating the FAVARX model.

B Estimation Details

B.1 QMLE for the Approximate Dynamic Factor Model

The approximate dynamic factor model can be cast into state-space form as follows:

$$y_t = \begin{pmatrix} \Lambda & 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-p+2} \\ f_{t-p+1} \end{pmatrix} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, R),$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-p+2} \\ f_{t-p+1} \end{pmatrix} = \begin{pmatrix} \Phi_1 & \Phi_2 & \cdots & \Phi_{p-1} & \Phi_p \\ I_r & 0_r & \cdots & 0_r & 0_r \\ \vdots & \vdots & & \vdots & \vdots \\ 0_r & 0_r & \cdots & 0_r & 0_r \\ 0_r & 0_r & \cdots & I_r & 0_r \end{pmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ \vdots \\ f_{t-p+1} \\ f_{t-p} \end{pmatrix} + \begin{pmatrix} I_r \\ 0_r \\ \vdots \\ 0_r \\ 0_r \end{pmatrix} \eta_t, \quad \eta_t \sim \mathcal{N}(0, Q),$$

where I_r is an r -dimensional identity matrix and 0_r is an r -dimensional matrix of zeros. For convenience, let F_t denote the state vector and Φ denote the state transition matrix. Note that, in addition to the assumption of Normally-distributed idiosyncratic components and factor innovations, R is assumed to be diagonal for the purposes of estimation. As discussed in the main text, possible model misspecification means that our estimates then correspond to QMLE.

Following Doz et al. (2012), QMLE is conducted using the EM algorithm and the Kalman filter-smoother. First, we initialise the Kalman filter-smoother recursions using the first r PCA-based estimates of the factors and OLS estimates of the parameters Λ , Φ , R , and Q , treating the PCA factors as the true common factors. Given these starting values, we then alternate between two steps. In the first step, we estimate the expected value of the common factors given the data and previously estimated model parameters, which involves running the Kalman filter-smoother recursions and getting the new estimate of the common factors denoted by $\mathbb{E}[F_t | Y_T; \hat{\theta}]$, where $Y_T = \{y_1, \dots, y_T\}$ and $\hat{\theta}$ is a vector of the estimated model parameters from the previous step.

This represents the “expectation” step of the algorithm. Then, in the second step, we compute new parameter estimates given the data and the updated estimates of the common factors. This represents the “maximisation” step of the algorithm. The second step makes use of the following formulas:

$$\begin{aligned}\Lambda^{(\text{new})} &= \left(\sum_{t=1}^T y_t \mathbb{E} \left[F_t' \mid Y_T; \hat{\theta} \right] \right) \left(\mathbb{E} \left[F_t F_t' \mid Y_T; \hat{\theta} \right] \right)^{-1}, \\ \Phi^{(\text{new})} &= \left(\mathbb{E} \left[F_t F_{t-1}' \mid Y_T; \hat{\theta} \right] \right) \left(\mathbb{E} \left[F_{t-1} F_{t-1}' \mid Y_T; \hat{\theta} \right] \right)^{-1}, \\ R^{(\text{new})} &= \text{diag} \left(\text{diag} \left(\frac{1}{T} \sum_{t=1}^T y_t y_t' - \Lambda^{(\text{new})} \mathbb{E} \left[F_t \mid Y_T; \hat{\theta} \right] y_t' \right) \right), \\ Q^{(\text{new})} &= \frac{1}{T-1} \left(\sum_{t=2}^T \mathbb{E} \left[F_t F_t' \mid Y_T; \hat{\theta} \right] - \Phi^{(\text{new})} \sum_{t=2}^T \mathbb{E} \left[F_{t-1} F_t' \mid Y_T; \hat{\theta} \right] \right).\end{aligned}$$

These two steps are repeated recursively until the algorithm converges. We judge convergence to be when c_m is less than 10^{-6} , with c_m given by:

$$c_m = \frac{\hat{\mathcal{L}}(\hat{\theta}_{(m)} \mid Y_T) - \hat{\mathcal{L}}(\hat{\theta}_{(m-1)} \mid Y_T)}{\left(\hat{\mathcal{L}}(\hat{\theta}_{(m)} \mid Y_T) + \hat{\mathcal{L}}(\hat{\theta}_{(m-1)} \mid Y_T) \right) / 2},$$

where $\hat{\mathcal{L}}(\hat{\theta}_{(m)} \mid Y_T)$ is the quasi-log-likelihood and $m = 1, \dots, M$ is the number of evaluations needed to achieve convergence up to a maximum M set by the researcher. We set $M = 500$, but the number of evaluations needed in all cases we considered was much less than 100. The quasi-log-likelihood $\hat{\mathcal{L}}(\hat{\theta} \mid Y_T)$ is evaluated as:

$$\begin{aligned}\hat{\mathcal{L}}(\hat{\theta} \mid Y_T) &= - \sum_{t=1}^T \left(\frac{1}{2} [y_t - \Lambda f_t]' R^{-1} [y_t - \Lambda f_t] \right) - \frac{T}{2} \log |R| \\ &\quad - \sum_{t=2}^T \left(\frac{1}{2} [F_t - \Phi F_{t-1}]' Q^{-1} [F_t - \Phi F_{t-1}] \right) - \frac{T-1}{2} \log |Q| \\ &\quad - \frac{1}{2} [F_1 - F_0]' P_0^{-1} [F_1 - F_0] - \frac{1}{2} \log |P_0| - \frac{T(p+r)}{2} \log(2\pi),\end{aligned}$$

with the initial state (F_0) and initial state variance (P_0) given by:

$$F_0 = (I_{rp} - \Phi) F_1^{\text{PC}},$$

$$\text{vec}(P_0) = (I_{rp^2} - \Phi \otimes \Phi)^{-1} \text{vec}(Q),$$

where F_1^{PC} is the first observation from PC-based factor estimate. See Ghahramani and Hinton (1996) for more details.

One issue with the model is the likelihood is invariant to any invertible linear transformation of the factors. This means that for any invertible matrix H , the parameters: $\theta = \{\Lambda, \Phi, R, Q\}$ and $\theta_H = \{\Lambda H^{-1}, H\Phi H^{-1}, R, HQH'\}$ are observationally equivalent and hence θ is not identifiable from the data. In order to achieve identifiability of θ , one needs to impose a particular identifying restriction. For our FAVARX analysis, we choose to implement the restriction “PC3” proposed by Bai and Ng (2013). This identifying restriction specifies the first $r \times r$ block of Λ to be an identity matrix:

$$\Lambda = \begin{pmatrix} I_r \\ \Lambda^* \end{pmatrix}$$

where Λ^* is an $(N - r) \times r$ unrestricted block of Λ . This parametrisation of Λ is also called the “named-factor” normalisation because it associates each factor with a specific variable (Stock and Watson 2016). When implementing this restriction we have to order the variables in our dataset so that the first r variables are the naming variables. In practice, the naming variables need to be reasonably different from each other and sufficiently representative of groups of other variables so that the innovations to their common components span the same space of the factor innovations. To impose this identifying restriction, we first estimate Λ as indicated previously and then set the first $r \times r$ block to be an identity matrix (see Bańbura and Modugno 2014).

A convenient feature of QMLE approach to estimating the approximate dynamic factor model is that the computational complexity of the Kalman filter-smoother recursions depends only on the size of the state vector, which in our case corresponds to the number of factors r times the order of the VAR p , but is independent of the cross-sectional dimension N . However, note that, while the EM algorithm will converge to a maximum, it is not guaranteed to find the global maximum,

but may instead converge to a local maximum. At the same time, the chance of this occurring can be offset by starting the algorithm, as we do, with the PCA estimates, which are consistent as $N \rightarrow \infty$.¹

The main reason we use this QMLE approach instead of PCA relates to its potential for improved efficiency when estimating the common factors. This comes from explicitly assuming the factor dynamics follow a VAR structure. Doz et al. (2012) show the efficiency improvements are relevant when there are multiple common factors to estimate. Furthermore, as a by-product of this approach, we get a measure of the precision of the estimates of the common factors via the state variance from the Kalman smoother, as seen in Figure 4 in the main text. Another desirable feature of this method (which we do not explore) is that it is capable of handling either missing or mixed frequency data (see Giannone et al. 2008).

B.2 Estimation of the FAVARX Model

Here we describe the FAVARX model estimation in greater detail. Our model has two blocks: a foreign block and a domestic block. The foreign block is modelled as exogenous to the domestic block in order to achieve identification of foreign shocks. This is a common identifying assumption used in SVAR models for small open economies such as Australia (for example, see Dungey and Pagan 2000; 2009) and reflects the idea that the domestic economy is too small to affect the foreign economy.

Let the foreign block be denoted by x_t and the domestic block by z_t . The foreign block contains, in the following order, the RBA index of commodity prices (ICP), U.S. real GDP growth, U.S. CPI inflation, and the U.S. Federal Funds Rate (FFR). The domestic block contains, in the following order, an $r \times 1$ vector of unobserved factors f_t that summarise domestic economic information, the Overnight Cash Rate (OCR), denoted by r_t , and the real TWI, denoted by q_t . We can think of the unobserved factors as possibly capturing variation in real economic activity or inflationary pressures that are not well proxied by any particular individual observed variable,

¹Stock and Watson (2002), Bai and Ng (2002), and Bai (2003) prove consistency of PCA estimation for approximate factor models.

but are important in a wide range of economic data series. Finally, assume the joint dynamics of x_t and z_t are given by the following equation:

$$\begin{pmatrix} x_t \\ z_t \end{pmatrix} = \sum_{i=1}^{p'} A_i \begin{pmatrix} x_{t-i} \\ z_{t-i} \end{pmatrix} + \epsilon_t,$$

where A_i is a matrix of VAR coefficients and the lag order p' is not necessarily the same as p for the approximate dynamic factor model. We impose block exogeneity in the model by zeroing out all the coefficients relating lags of the domestic variables to the foreign variables:

$$A_i = \begin{pmatrix} a_{11,i} & 0 \\ a_{21,i} & a_{22,i} \end{pmatrix}$$

We next assume that what Bernanke et al. (2005) call “informational” time series $\tilde{y}_t$ are related to unobserved factors f_t and observed “factors” $\{x_t, r_t, q_t\}$ by the equation:

$$\tilde{y}_t = \Lambda_x x_t + \Lambda_f f_t + \Lambda_r r_t + \Lambda_q q_t + e_t,$$

where Λ_x is $N \times 4$ vector of x_t loadings, Λ_f is an $N \times 2$ matrix of common factor loadings, Λ_r is an $N \times 1$ vector of r_t loadings, Λ_q is an $N \times 1$ vector of q_t loadings and e_t is an $N \times 1$ vector of error terms with mean zero that are assumed to display a small amount of cross-correlation. Note that $\tilde{y}_t$ excludes x_t , r_t , and q_t , as well as oil prices and the real OCR given their strong correlations with commodity prices and the OCR, respectively.

We consider only one approach to estimating the FAVARX, whereas Bernanke et al. (2005) consider two: one via PCA and the other via Bayesian estimation. We use their two-step method based on the estimator using PCA, but we replace this with QMLE estimates of the common factors based on the named-factor normalisation discussed in the previous subsection. Using QMLE estimates of common factors in a FAVAR has some precedence, as Bernanke and Boivin (2003) did something similar when considering a mixed-frequency dataset for the U.S. economy.

Denote the QMLE estimates for the common factors of $\tilde{y}_t$ by $\hat{C}(x_t, f_t, r_t, q_t)$, where the ordering of variables is important. Because $\hat{C}(x_t, f_t, r_t, q_t)$ corresponds to an arbitrary linear combination

of its arguments, obtaining estimates of the rotated unobserved factors $\hat{f}_t$ involves determining the part of $\hat{C}(x_t, f_t, r_t, q_t)$ that is not spanned by x_t , r_t , or q_t .

Because x_t , r_t , and q_t are not explicitly imposed as common components in the first estimation step, any of the linear combinations underlying $\hat{C}(x_t, f_t, r_t, q_t)$ could involve any of x_t , r_t , or q_t . Bernanke et al. (2005) argue that it would not be correct to simply estimate a VAR based on $\hat{C}(x_t, f_t, r_t, q_t)$ and identify the policy shock recursively. Instead, they stress that the direct dependence of the common factors of $\tilde{y}_t$ on x_t , r_t , and q_t must be removed beforehand.

If linear combinations implicit in $\hat{C}(x_t, f_t, r_t, q_t)$ were known, this would involve subtracting x_t , r_t , and q_t times the associated coefficient(s) from each of the elements of $\hat{C}(x_t, f_t, r_t, q_t)$. However, because they are unknown, Bernanke et al. (2005) propose to estimate the coefficients through a multiple regression of the form:

$$\hat{C}(x_t, f_t, r_t, q_t) = \beta_x x_t + \beta_{C^*} \hat{C}^*(f_t) + \beta_r r_t + \beta_q q_t + \nu_t,$$

where $\hat{C}^*(f_t)$ is an estimate of all the common components other than $\{x_t, r_t, q_t\}$. Bernanke et al. (2005) suggest one way to obtain $\hat{C}^*(f_t)$ is to extract factors from a subset of “slow-moving” variables designated in Appendix A, which by assumption are not affected contemporaneously by $\{x_t, r_t, q_t\}$. Then $\hat{f}_t$ is constructed as:

$$\hat{f}_t = \hat{C}(x_t, f_t, r_t, q_t) - \hat{\beta}_x x_t - \hat{\beta}_r r_t - \hat{\beta}_q q_t$$

after which a VAR in x_t , $\hat{f}_t$, r_t , and q_t is estimated using OLS.² Factor loadings can also be estimated based on a multiple regression for each variable in $\tilde{y}_t$ on x_t , $\hat{f}_t$, r_t and q_t .

The foreign and monetary policy shocks are identified recursively (i.e., using a Cholesky factorisation of the VAR innovation covariance matrix). Finally, because estimation involves the presence of generated regressors, we use the bootstrap of Kilian (1998) and 1,000 replications to compute confidence bands for the impulse response functions displayed in Section 4 of the main text.

²OLS estimation is done in two parts. First, we regress x_t on its own lags and a matrix of zeros with 3 columns similar to the domestic block of variables, i.e., $\{x_{t-1}, 0\}$. Second, we regress z_t on lags of both foreign and domestic variables, i.e., $\{x_{t-1}, z_{t-1}\}$. Then we combine the coefficient estimates from these regressions to form our A_i coefficient matrices.

C Additional Figures

Figure A1: Test statistics for a break in the factor structure based on PCA estimated factors

Figure A2: QMLE factors vs. PCA factors

Figure A3: Comparison of realised measures of common and idiosyncratic volatility for full-sample vs. subsample factor estimation

Figure A4: Original QMLE factors vs. factors based on a “named-factor” normalisation

Figure A5: Original QMLE factors vs. factors for the “slow-moving” subset of variables

Figure A6: Rotated factors for the “slow-moving” subset of variables vs. initial factors for the “slow-moving” subset of variables

Figure A7: Responses to a monetary policy shock for the FAVARX model with factors estimated using the subset of “slow moving” variables

Figure A8: Responses to a monetary policy shock for FAVARX model with output gap vs. real GDP growth

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