A Factor Model Analysis of the Effects of Inflation Targeting on the Australian Economy*

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Abstract

We conduct factor model analysis of the Australian economy to examine how inflation targeting has affected common movements in macroeconomic variables. Compiling a panel dataset with 104 variables, we find that the Australian economy has a similar factor structure to other economies, with a sizeable portion of macroeconomic fluctuations accounted for by two common factors that have clear "real" and "nominal" interpretations based on their factor loadings. The factor structure appears to have permanently changed around the introduction of inflation targeting in 1993, with a large reduction in the volatility of common movements in macroeconomic variables compared to idiosyncratic movements, but with no abrupt changes in loadings for the common factors. Estimates for a factor-augmented vector autoregressive model with two common factors and the policy interest rate suggest that the transmission of monetary policy shocks changed with the introduction of and during the inflation targeting era, with no remaining price puzzle and an apparent flattening of the Phillips Curve since the mid 2000s.

Keywords: Inflation targeting; Monetary policy; Factor modelling; Structural change

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

*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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1 Introduction

A quick look at the data in Figure 1 makes it clear that the introduction of inflation targeting corresponded to a stabilization of the level of CPI inflation in Australia around the numerical target range of 2-3% introduced by the Reserve Bank of Australia (RBA) in 1993 (Stevens 1999). An important question is whether inflation targeting had other effects on the Australian economy such as changing common movements in macroeconomic variables, including those related to the transmission of monetary policy shocks. Factor modelling provides a powerful and flexible way to investigate this empirical question in a data-rich environment.[1]

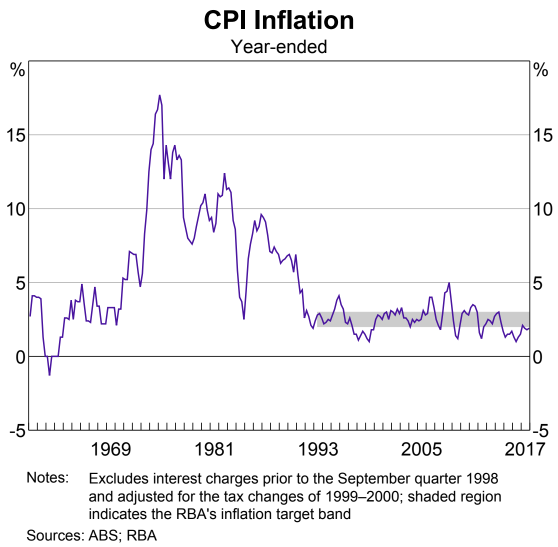


Figure 1: CPI inflation in Australia from 1960-2017

We compile a large panel of macroeconomic data for the Australian economy and conduct factor model analysis to investigate the effects of inflation targeting. Our analysis suggests that a sizeable portion of macroeconomic fluctuations for Australia can be captured by two common factors. This result is the same as what was found for the U.S. economy by Stock and Watson (2005) and many others. Standard selection criteria suggest the need for between 2-4 common factors, with recursive estimates generally suggesting a possible decline in the number of common factors following the introduction of inflation targeting. This possible decline stands in contrast to findings for the U.S. economy by Bai and Ng (2007) of a possible

[1]See Stock and Watson (2016) survey on factor modelling and its use in examining the effects of structural shocks.

increase. A change in the number of factors is indicative of a change in the factor structure, with a decline implying a different type of structural change than an increase. We explore the particular nature of changes in the factor structure of the Australian economy in detail.

Based on the standard selection criteria, we estimate an approximate dynamic factor model of the Australian economy with three common factors. The estimation is based on quasi maximum likelihood, as in Doz et al. (2011; 2012). Our estimates suggest that only two common factors explain a sizeable portion of macroeconomic fluctuations and they have clear "real" and "nominal" interpretations based on their factor loadings. We apply a recent test developed by Han and Inoue (2015) for a structural break in factor loadings and find a significant break, with the test statistics for two versions of the test maximized just before and after the introduction of inflation targeting in mid 1993 (Stevens 1999; 2003). Notably, both versions of the test would still be significant if the break were in 1993Q1, corresponding to the introduction inflation targeting in the next quarter, with 1993Q1 close to the earliest date at which both test statistics are significant. Meanwhile, there is no evidence for additional structural breaks once accounting for the break at the estimated dates or in 1993Q1.

Looking at the cross-sectional variation in the common and idiosyncratic components of macroeconomic variables before and after the introduction of inflation targeting, it is clear that there was a much larger reduction in the volatility of common components than idiosyncratic components. That is, inflation targeting has not just stabilized the level of inflation, but it also appears to have stabilized the common components of macroeconomic variables. This reduction in common volatility is broad based, applying to both real and nominal variables. Meanwhile, the fact that idiosyncratic components have remained relatively volatile suggests that signal-to-noise ratios for common and idiosyncratic movements in variables such as CPI inflation have declined, making the benefit of using factors rather than proxying for common real and nominal fluctuations with noisy variables even greater during the inflation targeting era. Interestingly, recursive estimates of factor loadings for real GDP growth, CPI inflation, and the OCR policy interest rate suggests a stabilization rather than an abrupt change with the introduction of inflation targeting. This argues against a "Type 1" break in the terminology of Han and Inoue (2015) in which there is a change in cross-correlations related to common factors or, equivalently, an increase in the number of relevant factors. Instead, it is consistent with a change in the volatility of factors or, equivalently, a decrease in the number of of relevant factors, consistent with our recursive estimates of the number of factors.

The results for the approximate dynamic factor model motivate us to consider a factor augmented vector autoregressive (FAVAR) model in order to investigate possible changes in the transmission of monetary policy shocks following the introduction of inflation targeting. Even if cross correlations of variables related to factors are relatively stable, shock identification will still be affected given changes in relative variances. For identification of monetary policy shocks, we follow Bernanke et al. (2005) and use estimated loadings to relate the full panel to a three-variable structural vector autoregressive (SVAR) model that includes the "real" and "nominal" factors from our approximate dynamic factor model and the policy interest rate. Importantly, the two common factors are re-estimated from a subset of the panel that corresponds only to "slow moving" variables that should only respond with a lag to a monetary policy shock. We find that a contractionary monetary policy shock temporarily lowers real activity and inflation, with the "price puzzle" almost completely resolved, as was found by Bernanke et al. (2005) for the U.S. data.[2] The accumulated response of log CPI levels off at a 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). Structural break tests based on Qu and Perron (2007) suggest possible changes in VAR parameters around the introduction in inflation targeting and the Global Financial Crisis. Subsample estimates suggest no remaining price puzzle and a flattening of the Phillips Curve since the mid 2000s.

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 stabilizing the level of inflation, but also appear to involve reducing the common volatility of macroeconomic variables. This link in timing of a reduction in macroeconomic volatility with inflation targeting would be obscured somewhat by looking at real GDP growth on its own, but is clear from the factor analysis. Related, because idiosyncratic volatility has not reduced by as

[2]See Bishop and Tulip (2017) on the challenges in removing the price puzzle for Australian SVARs.

much as common volatility, our results suggest benefits to measuring real activity and price pressures using a factor modelling approach. The mitigation of a price puzzle for our FAVAR model provides an example of such a benefit. Despite apparent changes in the transmission of monetary policy, the factor modelling approach also allows for relatively precise estimation of the effects of a monetary policy shock in a data rich environment and the possibility to relate the effects of policy to any variable in the panel, as well as any other variable that may only be available more recently due to data limitations, but for which we can estimate factor loadings. One clear implication of our FAVAR estimates is that the RBA currently pursues inflation targeting in line with its mandate, rather than price level targeting. Another clear implication is that, consistent with a flattening of the Phillips Curve, the implied sacrifice ratio appears to have increased since the mid 2000s.

The rest of this paper is organized as follows. Section 2 discusses the panel dataset, investigates the relevant number of common factors, presents estimates for an approximate dynamic factor model, and conducts break tests for the factor structure of the Australian economy. Section 3 examines the effects of inflation targeting on the factor structure of the Australian economy and draws some implications for monetary policy. Section 4 directly investigates possible changes in the transmission of monetary policy shocks by estimating a FAVAR model and considers changes with the introduction of and during the inflation targeting era, again drawing implications for monetary policy. Section 5 concludes. Full details of the dataset and estimation methods are provided in an appendix.

2 A Factor Model of the Australian Economy

2.1 An Australian macroeconomic panel dataset

We expand the panel datasets in Gillitzer et al. (2005) and Gillitzer and Kearns (2007) to cover 104 time series variables for the Australian economy from 1976Q4–2017Q2.[3] Due to

[3]Gillitzer et al. (2005) and Gillitzer and Kearns (2007) focus on smaller panels and extracting a single coincident business cycle index for the Australian economy rather than looking at the impact of inflation targeting on the factor structure of the economy. Similarly, Sheen et al. (2015) construct a daily coincident

data availability issues, the broader coverage of variables necessitates a later starting point for the sample than in Gillitzer et al. (2005) and Gillitzer and Kearns (2007). However, the sample still includes 15 years before the introduction of inflation targeting in mid 1993 and nearly 25 years since its introduction.

Because many of the raw data series are nonstationary, we transform variables by taking logs and/or first differences, as appropriate. As part of the transformation, we allow for a structural break in the mean levels of the price growth series in 1993Q1, corresponding to introduction of inflation targeting. This renders all of these series stationary without needing to take second differences. Once transformed to be stationary, we standardize all series by removing any remaining sample mean and dividing by the sample standard deviation. This gives each variable implicit equal weight in fitting with a factor model.

In terms of broad categories, 42% of the panel corresponds to real activity variables, 19% to price variables, and 15% to financial variables. Table 1 provides a more detailed breakdown into categories that we will refer to when looking at panel R^2s for factors. Meanwhile, a list of all variables and their corresponding data transformations is provided in the appendix.

Table 1: Number of variables by category

Category	Number
Expenditure	20
Production	19
Income	5
Employment	8
Surveys	5
Building & Capex	5
Overseas Transactions	5
Prices	20
Money & Credit	6
Interest Rates	8
Misc	3
Total	104

Note: 'Misc' includes Share Price Index, Real TWI, and the Southern Oscillation Index.

index using mixed frequency modelling of a smaller-scale dynamic factor model.

2.2 How many common factors?

Figure 2 displays the “scree plot” for the Australian macroeconomic panel dataset based on principle components analysis (PCA).[4] It provides a simple diagnostic for a likely number of relevant common factors. The largest two eigenvalues from PCA explain much more variation than all the remaining eigenvalues. This is suggestive of two relevant common factors that capture about 13% and 9%, respectively, of the joint variation in the macroeconomic variables, with the remaining “scree” likely corresponding to much less important common factors or even idiosyncratic movements in some of the individual variables. This finding of two dominant common factors is consistent with findings for datasets from other countries, including for the U.S. economy by Stock and Watson (2005).

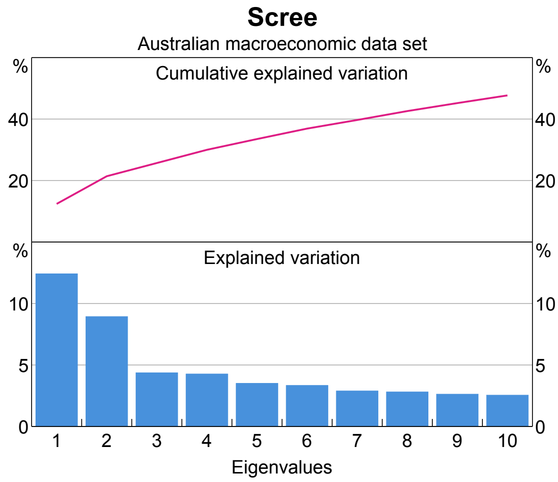


Figure 2: Scree plot based on PCA for the Australian macroeconomic panel dataset

Table 2 reports formal selection criteria results for the number of common factors. 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 is actually sufficient for the dataset. Starting with Bai and Ng (2002), formal selection criteria have been developed to determine the number of relevant common factors in a given dataset. The results in Table 2 capture this uncertainty about the number

[4]The typical shape of a scree plot as having a steep drop off in explained variation after the first few eigenvalues and then a more shallow long tail for the remaining eigenvalues is thought to be visually reminiscent of the side of a mountain after an avalanche, with the flattened out rubble at the base of the mountain corresponding to the “scree”.

of common factors. While a majority of criteria select two common factors, there could be as many as seven relevant common factors.

For our approximate factor model, we consider three common factors. We do so as a compromise between the 2-4 common factors suggested by the two Bai and Ng (2002) criteria. As will be seen with our estimates, two common factors appears to be sufficient to capture the main common variation in the dataset, but allowing for three common factors in the model makes this clear. Meanwhile, any evidence of more than three common factors, such as suggested by the Onatski (2010) criterion, could reflect changes in the factor structure, which we will also investigate in full detail.

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 in looking at possible changes in the factor structure, Figure 3 reports recursive (expanding window) estimates of the number of common factors.[5] The end-of-sample estimates are the same as what is reported in Table 2. However, what is notable about the recursive estimates is that the particular criteria which imply a larger number of common factors show a decline during the inflation targeting era since 1993Q1. Notably, this decline contrasts with findings by Bai and Ng (2007) for the U.S. economy of an increase in recent years. Instead, it is consistent with a particular type of structural change in which the factor structure simplifies over time due to an elimination of common variation and, thus, corre-

[5] We prefer recursive to rolling-window estimates because they better illustrate possible permanent changes in the structure, while rolling windows could capture possible recurring changes, but are sensitive to the window size. For recurring changes, the 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.

sponds to a reduction in volatility rather than a change in cross correlations explained by common factors. Again, we will investigate this possibility in full detail.

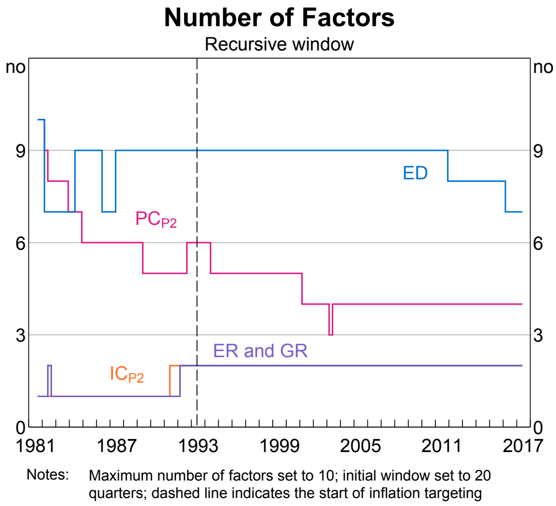


Figure 3: Recursive estimates of the number of common factors

2.3 Estimation and interpretation

Based on the Bai and Ng (2002) selection criteria, we estimate an approximate dynamic factor model with three common factors:

$$Y_t = \Lambda F_t + \epsilon_t, \tag{1}$$

with $F_t = \Phi(L)F_{t-1} + \eta_t$, where Y_t and ϵ_t are $N \times 1$, Λ is $N \times 3$, F_t and η_t are 3×1, and $\Phi(L)$ is a 3×3 VAR lag polynomial. An approximate dynamic factor model allows the elements of ϵ_t to be weakly dependent across series and time, but they are uncorrelated with the common factors, $\mathbb{E}\left[\epsilon_t \eta'_{t-k}\right] = 0$, $\forall\, k$.[6]

We conduct initial "static" estimation using PCA, following (Stock and Watson 2005).[7]

[6]Labeling this model as "dynamic" follows Doz et al. (2011; 2012) and reflects the fact that estimation explicitly accounts for the dynamic VAR structure for the factors, rather than an alternative notion of a "dynamic" factor model having non-zero loadings for variables on lags of factors. Of course, the model we consider could allow for lagged relationships between variables and factors by including any lagged dynamic factors as additional "stacked" factors in F_t.

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

Then, using these static estimates, we calculate dynamic factor estimates using quasi maximum likelihood estimation (QMLE) for a VAR of the factors with one lag based on SIC and Kalman filter-smoother recursions via the EM algorithm, following (Doz et al. 2011; 2012). See the appendix for more details.

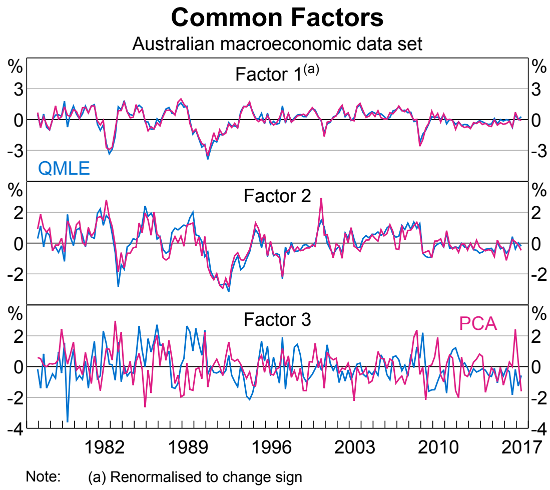


Figure 4: QMLE vs. PCA factor estimates

Figure 4 displays the static and dynamic estimates of the three common factors.[8] There is a strong coherence between the estimates for the first two factors, which display considerable persistence. There is less obvious a link between the estimates of the third factor, which appears to be far less persistent. An explanation could be that the static estimates of the third factor captures some lagged dynamics of the first two factors, but is mostly just noise when considering dynamic factor estimation with a VAR(1) structure. Meanwhile, the dynamic estimates of the third factor turn out to explain very little variation of the panel dataset.

[8]We renormalize the sign of the first factor such that real GDP growth has a positive loading on it for ease of interpretation as a real activity factor.

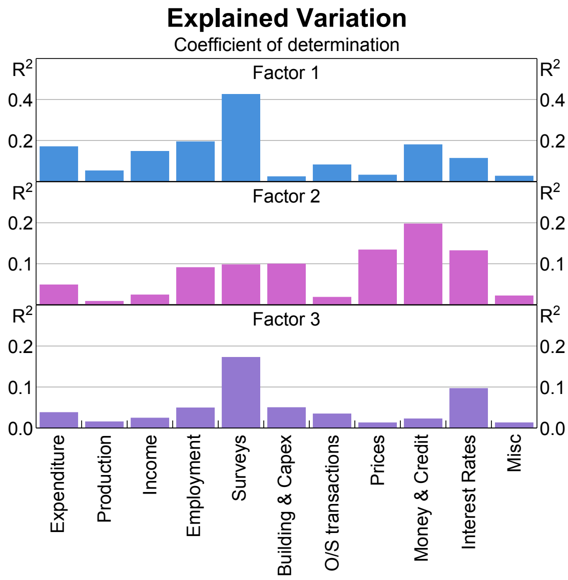


Figure 5: Average R^2 statistics by category

Figure 5 reports the variation of data in different categories explained by the common dynamic factors based on panel R^2s that capture the fraction of the variance of a series explained by a given common factor. The fact that these are all reasonably low suggests that variables in each category are subject to considerable idiosyncratic variation. It is also clear based on the categories that the first factor corresponds more to "real" variables such as measures of expenditure, employment, and activity surveys, while the second factor corresponds more to "nominal" variables, such as prices, money, credit, and interest rates. Notably, we find that interest rate spreads in particular load on both factors, which likely reflects their information content about both real activity and inflation. As mentioned above, the third factor explains very little variation of the panel, with the highest R^2s corresponding to activity surveys and interest rates. Thus, it may capture something about expectations of future real activity or "sentiment", but is possibly just noise that can be dropped from the model.

2.4 Breaks in the factor structure?

As noted above, one reason why some selection criteria might suggest more than two factors could be due to changes in the factor structure. We formally test for structural breaks using an approach recently proposed by Han and Inoue (2015).[9] The null hypothesis of their test is that all factor loadings are constant over time against 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. Han and Inoue (2015) note that a change in the volatility of factors or in factor loadings are not separately identified, so a rejection could reflect either or both. The idea of a change in factor loadings in the sense of being equivalent to additional factors in a PCA setting corresponds to a "Type 1" break, where the change in the factor structure reflects a change in cross-correlations between variables related to common factors. By contrast, the idea of a change in the volatility of factors corresponds to a "Type 2" break, where the change in the factor structure reflects a change in the volatility of variables related to common factors, but with the same cross-correlations between variables related to common factors. Our earlier finding of a reduction in the number of factors implied by 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.

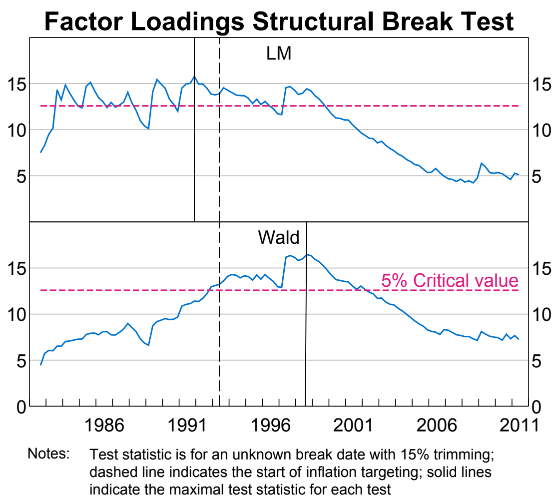


Figure 6: Han and Inoue (2015) structural break test statistics

Figure 6 plots the Han and Inoue (2015) LM and Wald test statistics for a structural break

[9]Breitung and Eickmeier (2011) and Chen et al. (2014) also propose tests for structural instability in factor models. However, both of these alternative tests have drawbacks. For example, Breitung and Eickmeier's (2011) joint test 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).

in factor loadings. In both cases, we can reject the null of no break, with the LM test statistic maximized in 1991Q4 and the Wald test statistic maximized in 1998Q3. Notably, however, both test statistics are still significant if the break occurred in 1993Q1 with the introduction of inflation targeting, which is close to the earliest date at which both test statistics are significant. Thus, the results for Han and Inoue's (2015) test are consistent with the idea that the introduction of inflation targeting led to a change in the factor structure of the Australian economy. Furthermore, we note that the there is no support for an additional break, whether the first break is set to have occurred at the estimated dates or in 1993Q1. Given a break in the factor structure around the time of the introduction of inflation targeting, we turn next to an investigation of what effects it had on the Australian economy.

3 Effects of Inflation Targeting

3.1 Decline in common shocks

We find that the introduction of inflation targeting corresponded to a much larger reduction in the volatility of common components of macroeconomic time series than idiosyncratic components. To see this, we calculate the cross-sectional variance of common components, which reflects the variability of common factors, and of idiosyncratic components, which reflects the residual variability of the data, at each point of time. Figure 7 plots measures of common and idiosyncratic volatility over the whole sample for i) all of the variables, ii) just real variables, iii) just nominal variables, and iv) just price variables. The pattern is consistent in all of the cases. Although there are still peaks in the volatility measures after the introduction of inflation targeting that seem to be related to events such as the introduction of the GST in 2000 (idiosyncratic volatility) and the Global Financial Crisis in 2007-2009 (both common and idiosyncratic volatility), there is clearly lower average common volatility since the introduction of inflation targeting. The absence of a recession in Australia since the introduction of inflation targeting could help explain the relative lack of peaks in common volatility that occurred with the recessions in the early 1980s and 1990s. However, the common volatility is still generally lower after the introduction of inflation targeting than it was even during expansions prior to inflation targeting. Furthermore, contrary to recessions being the primary driver of volatility, the idiosyncratic volatility only looks slightly lower on average since the introduction of inflation targeting, and this is not even clear for the price variables. Meanwhile, because the reduction of idiosyncratic volatility is not as large as common volatility, signal-to-noise ratios for individual variables proxying for the common factors have clearly dropped since the introduction of inflation targeting.

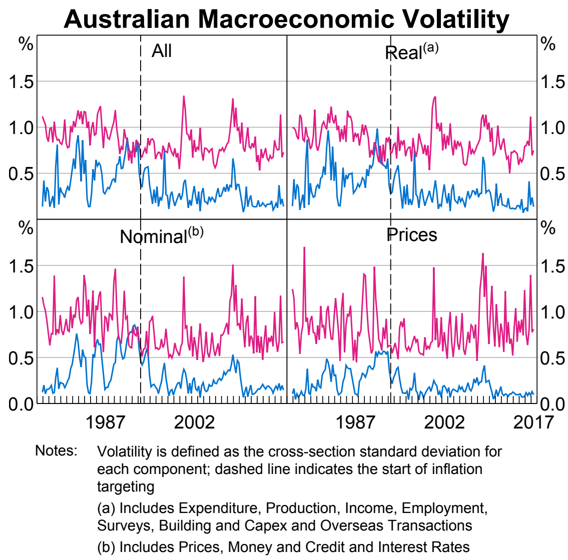


Figure 7: Common vs. idiosyncratic variation in the panel

Figure 8 illustrates a decline in signal-to-noise by plotting the common and idiosyncratic components of (adjusted and standardized) CPI inflation. The variation in both components seems to have lessened somewhat, but much more so for the common component. Thus, a higher proportion of the quarterly fluctuations in CPI inflation reflect noise since the introduction of inflation targeting. A direct implication for monetary policy is that it makes sense to "look through" some of the high frequency movements in CPI inflation as reflecting noise rather than a persistent change in underlying inflationary pressures. Furthermore, the dynamic factor model provides a way to extract a signal about underlying inflationary pressures from a noisy series such as CPI inflation.

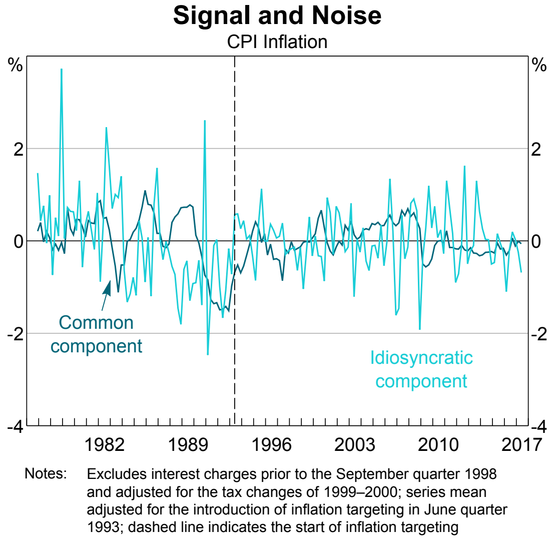


Figure 8: Common and idiosyncratic components of CPI Inflation

To further investigate the nature of the change in the factor structure with the introduction of inflation targeting, we calculate recursive estimates of factor loadings for real GDP growth, CPI inflation, and the OCR policy interest rate on the estimated factors.[10] Figure 9 plots these recursive estimates along with 95% confidence bands.[11] Real GDP growth loads significantly on all three factors, CPI inflation only loads significantly on the second factor, and the OCR loads significantly on the first two factors. 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. The estimated loadings for the third factor are positive for real GDP growth and effectively zero for CPI inflation and the OCR, suggesting it could reflect high frequency real activity movements that do not spill over into inflation or affect monetary policy. Meanwhile, it is quite notable that the recursive estimates of the factor loadings seem to stabilize rather than jump with the introduction of inflation targeting. This is consistent with "Type 2" break in Han and Inoue (2015) for which the break reflects a change in the volatility related to factors rather

[10]Again, we focus on recursive rather than rolling-window estimates in order to better understand possible permanent changes rather than possible temporary changes, as well as to avoid having to make an arbitrary choice about the window size.

[11]Confidence bands are based on inverted t tests using the alternative HAC standard errors proposed in Hartigan (2018)

than a change in cross-correlations related to factors under a "Type 1" break.

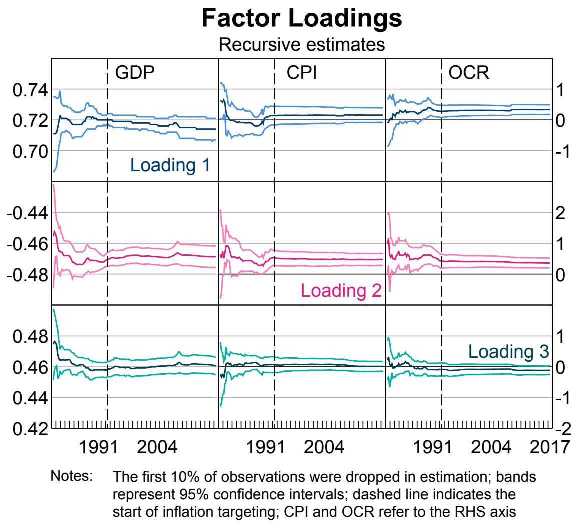


Figure 9: Stability of factor loadings

The structural break analysis suggests that inflation targeting has done more than just stabilize the level of inflation in Australia. It has also reduced the volatility of common movements in macroeconomic variables and possibly reduced the number of common factors in the economy. This reduction in volatility is not just in price growth 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.[12] Notably, 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 implied by looking at real GDP growth on its own, directly suggesting a benefit of factor analysis.[13]

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

[13]Break date estimates are 1984Q1 and 1998Q4 using the Bai and Perron (1998) sequential test procedures for squared demeaned real GDP growth regressed on a constant and allowing for HAC standard errors. Without HAC standard errors, the evidence is only for one break in 1984Q1, corresponding to the so-called "Great Moderation" that has been argued to have occurred in Australia around the same time as in the United States (Summers 2005). Interestingly, if we use Qu and Perron (2007) sequential test procedures for structural breaks in mean and/or variance of real GDP growth, we only find evidence of one break in variance in 1998Q4, with or without HAC standard errors, closely corresponding to the estimated timing for the Wald test statistic of a break in factor loadings in Figure 6. However, if we estimate two breaks in variance, the estimated break dates are 1984Q1 and 1998Q4, as was found with the Bai and Perron (1998) procedures. Furthermore, reflecting the presence of idiosyncratic noise, a change in volatility in real GDP growth in 1998Q4 is far less visually evident than the common volatility changes with the introduction of inflation targeting in Figure 7.

In addition, the larger drop in the volatility of common components relative to idiosyncratic components implies an increased benefit of looking at common factors to eliminate noise in individual observed variables. Notably, price measures, including the RBA's numerical target variable CPI inflation, have particularly large idiosyncratic components, while our factor model estimates suggests that the RBA can "look through" most quarterly fluctuations in these measures and focus on underlying measures such as the common component of price growth variables provided by our dynamic factor model.

The stability of the factor loadings is reassuring for the use of a factor model to capture "real" and "nominal" fluctuations in the Australian economy. However, even with stable loadings, changes in relative variances of shocks in the economy can result in changes in the dynamic interactions of variables. For example, the transmission of monetary policy shocks may have changed with the introduction of inflation targeting. We turn to this issue next.

4 Transmission of Monetary Policy

Based on apparent factor structure of the Australian economy, we develop a FAVAR model to examine the transmission of monetary policy shocks, including possible changes due to the introduction of inflation targeting.

4.1 A FAVAR model

Following Bernanke et al. (2005, BBE), we estimate a FAVAR model based on BBE's preferred specification of using the policy interest rate as an "observed" factor. The model uses factor loadings to relate the full panel of data to a three-variable VAR that includes the first two common factors corresponding to "real" and "nominal" fluctuations and the OCR policy interest rate. As in BBE, we extract the factors from a subset of panel that corresponds only to "slow moving" variables (i.e., it excludes, for example, survey measures, oil prices, commodity prices, financial variables, and the exchange rate – the full list is given in the dataset table in the Appendix). Crucially, the panel excludes the OCR policy rate and the factors are "rotated", as in BBE, to remove any residual effects of the policy rate. Despite these changes, the extracted factors are very similar to the original factors estimated from the full panel, as can be seen in Figure 10. Then, monetary policy shocks are identified by assuming they are contemporaneously uncorrelated with other shocks that drive the factors.[14] See the appendix for full details.

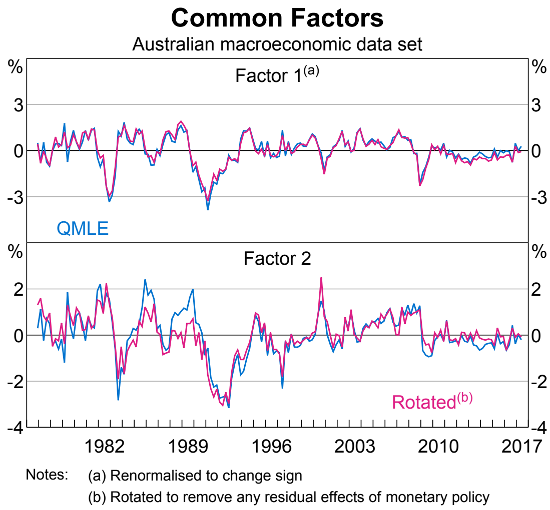


Figure 10: Original vs. rotated factors from restricted panel

4.2 Full sample estimates

Before considering structural change, we start by estimating a FAVAR with two lags based on SIC for the full sample of 1976Q4–2017Q2 to provide benchmark results. Given FAVAR parameter estimates, we calculate impulse response functions (IRFs) for a surprise 25bps increase in the OCR policy rate, with reported 95% confidence bands based on 500 bootstrap replications.

Figure 11 plots IRFs for the OCR and the two factors. The OCR increases 25bps on impact, by construction, and then it gradually reverts back to its initial level, while both factors contract significantly at business cycle horizons. Given the loadings for these factors (real

[14] In practice, this identification involves ordering the OCR policy rate last in the VAR and using a Cholesky factorization of the forecast error variance-covariance matrix to identify monetary policy shocks. However, due to the consideration of factors and their "rotation", the correlation between the forecast error for the VAR are very low, so ordering has very little effect on the identified shocks.

GDP growth positive on the first factor and CPI inflation positive on the second factor), these results are consistent with the interpretation of the identified monetary policy shock as being "contractionary".

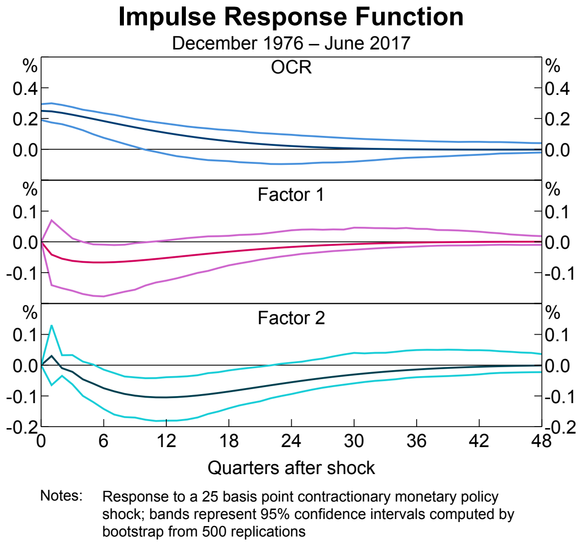


Figure 11: Impulse response functions for the OCR and the two factors

Figure 12 directly examines the implied IRFs for real GDP growth and CPI inflation. The point estimates still show contractionary effects, although the response of real GDP growth is no longer significant, reflecting the fact that real GDP growth also loads negatively on the second factor in addition to positively on the first factor. The response of CPI inflation is very similar to the response of the second factor, reflecting an insignificant loading of CPI inflation on the first factor. Accumulated responses are also reported to show the implied effects of a monetary policy shock on the log levels of the real GDP and CPI. Consistent with long-run monetary neutrality, there is no significant long-run effect on log real GDP. Meanwhile, log CPI is permanently lower following the contractionary monetary policy shock. This reflects the dynamics of the OCR in response to policy shock, with the RBA gradually returning the policy rate back to its original level, but not overshooting in order to reverse the initial effects of the shock on the price level. That is, the IRFs are consistent with the RBA targeting the inflation rate, not the price level, by letting "bygones be bygones" (Stevens 1999).

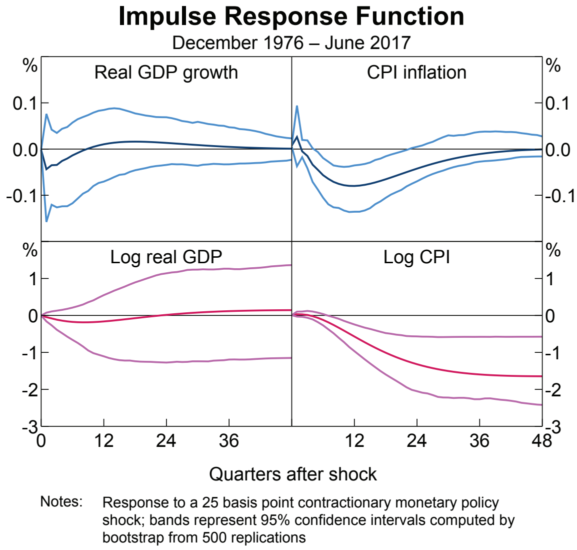


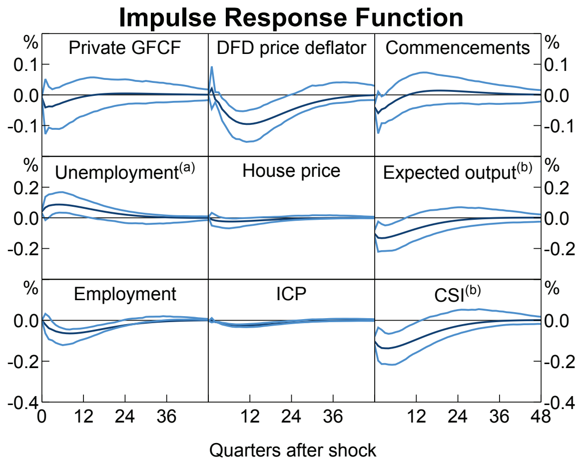
Figure 12: Impulse response functions for real GDP and CPI

The point estimate for the response of CPI inflation to a contractionary monetary policy shock is slightly positive at the one-quarter horizon. However, it is insignificant and the point estimates are negative and often significantly so at subsequent horizons. Thus, these IRFs largely resolve the so-called "price puzzle", as BBE did with their FAVAR for the U.S. economy.[15] The price puzzle has been particularly challenging to solve for Australian SVARs, as discussed in Bishop and Tulip (2017). So our result of effectively no price puzzle is particularly encouraging for using a FAVAR to estimate the effects of monetary policy shocks on the Australian economy.

A benefit of the FAVAR model is that it allows us to examine the effects of a monetary policy shock on any variable in the panel (and even variables not in the panel due to limited data availability, as long as we can determine relevant loadings on the factors). Figure 13 plots the IRFs for a selection of other variables that reflect different aspects of the Australian economy. The variables are private investment, the domestic final demand (DFD) deflator, housing commencements, the unemployment rate, established house prices, a survey of expected output, total employment growth, an index of commodity prices (ICP), and a consumer sentiment index (CSI). The series are transformed to be stationary when appropriate and

[15] The price puzzle is the tendency for estimated IRFs to initially show a positive response of inflation to a contractionary monetary policy shock. It is often seen as a failure to identify a true shock rather than an endogenous response of the policy rate to other shocks, although it could reflect a genuine economic response in the case where inflation expectations are not anchored (see Lubik and Schorfheide 2003).

as noted in the figure. The IRFs behave as would be expected given a contractionary monetary policy shock. For example, DFD price deflator inflation behaves very similarly to CPI inflation, the unemployment rate increases significantly at business cycle horizons, and consumer sentiment falls significantly at business cycle horizons.



Notes: Response to a 25 basis point contractionary monetary policy shock; bands represent 95% confidence intervals computed by bootstrap from 500 replications; response for each series mapped via factor loadings; all series are growth rates besides those indicated otherwise

(a) First difference

(b) Level

Figure 13: Impulse response functions for other macroeconomic variables

4.3 Breaks in the FAVAR?

Given the benchmark full sample results, we now consider whether the introduction of inflation targeting changed the FAVAR parameters or whether they changed at any other point of the sample. To test for structural breaks in the FAVAR, we apply the Qu and Perron (2007) procedures. In principle, the methods in Qu and Perron (2007) can be applied to a linear system of regression equations with multiple structural breaks in mean and/or variance. However, given the large number of parameters for the FAVAR model, we need to apply tests for structural breaks equation-by-equation. Tables 3 and 4 report the results of supLR tests and sequential tests for each equation of the VAR portion of the model allowing for breaks in conditional mean and variance. Given a VAR setup, we assume no residual serial correlation. We consider a maximum of 3 breaks with 15% trimming from sample endpoints and between breaks.

The results support the existence of structural change in all three dynamic equations of the FAVAR, with the sequential tests providing some insight into the number and timing of the breaks. For the first factor, there appears to be two breaks, estimated to have occurred in 1990Q1 and 2010Q2. For the second factor, there appears to be one break, estimated to have occurred in 2011Q1. For the OCR, there appears to be two breaks, estimated to have occurred in 1990Q3 and 2011Q1.

Table 3: Qu and Perron (2007) SupLR Test

	Statistic			Critical value
Number	Factor 1	Factor 2	OCR	5%
1	43.31	45.77	197.80	24.21
2	78.91	69.89	268.87	40.09
3	99.33	91.23	290.40	55.00

Notes: Test is for a break in the conditional mean and variance. The number of breaks tested for is 3. The trimming parameter is set to 0.15. The total number of parameters in each model is 8.

Table 4: Qu and Perron (2007) Seq($\ell + 1 \mid \ell$) Test

	Statistic						Critical value
Seq($\ell + 1 \mid \ell$)	Factor 1	H_0 Date	Factor 2	H_0 Date	OCR	H_0 Date	5%
Seq(2 | 1)	35.60	1990:Q1	24.12	2011:Q1	71.07	1990:Q3	26.58
Seq(3 | 2)	22.93	2010:Q2	-	-	26.49	2011:Q1	27.58

Notes: Test is for a break in the conditional mean and variance. The number of breaks tested for in each equation is 3. The trimming parameter is set to 0.15. The total number of parameters in each model is 8.

Figure 14 reports 95% confidence sets for the structural break dates.[16] The confidence sets vary considerably in their precision for the different variables. However, the results broadly suggest that we should account for two breaks in the FAVAR, with the first break around the introduction of inflation targeting and the second break around the Global Financial Crisis. Technically, the introduction of inflation targeting occurred just after the apparent timing of the first break for the first factor and the OCR based on the 95% confidence sets (the data are not informative at all about the timing of a break for the second factor). However, for simplicity of interpretation and because 1993Q1 is within 99% confidence sets, we consider our first subsample for the FAVAR to be up to the introduction of inflation targeting, although our FAVAR estimates would be similar if we used either of the earlier

[16]Confidence sets are based on inverted likelihood ratio tests proposed in Eo and Morley (2015).

estimated break dates in 1990. For the second break, we find the FAVAR estimates are highly imprecise using only data after the Global Financial Crisis, which is likely due to few surprise changes in the OCR during this period. If we extend the subsample back to begin in the mid 2000s, which is consistent with 95% confidence sets for the two factors and a 99% confidence set for the OCR, the FAVAR estimates are relatively more precise. Thus, we consider the last subsample for our FAVAR to begin in 2005Q1, which is consistent with earliest second break for the first factor in the 95% confidence set. The results would be similar, but increasingly less precise, if we moved the start of the last subsample to later in the mid 2000s.

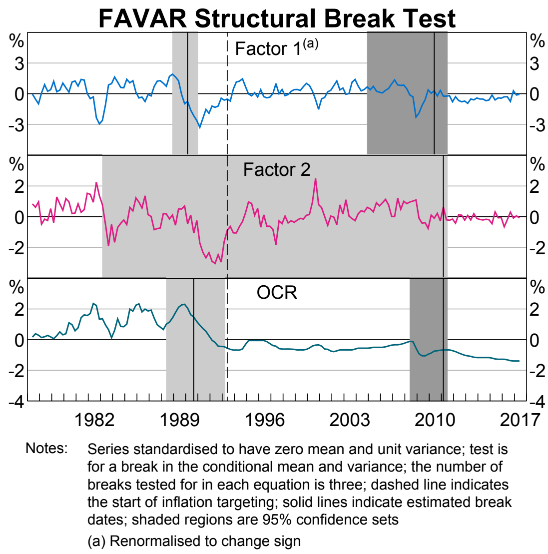


Figure 14: Estimated structural breaks in FAVAR equations and 95% confidence sets

4.4 Sub-Sample FAVAR Analysis

Based on the structural break test results, we split the sample into three regimes: pre inflation targeting, 1976Q4-1993Q1; early inflation targeting, 1993Q2-2004Q4; and late inflation targeting, 2005Q1-2017Q2. The apparent changes in the VAR parameters motivate our consideration of this subsample analysis. In particular, a change in any of the reduced-form slope coefficients or cross-correlations for the forecast errors should lead to different identified structural shocks for the FAVAR and, therefore, different IRFs.

Looking at the top row of Figure 15, the dynamics of the OCR following a contractionary shock have changed considerably over the full sample of 1976Q4-2017Q2. In the pre inflation targeting period, the RBA appeared to quickly bring the OCR back to its previous level and even significantly lowered it for a while afterwards. In the early inflation targeting period, the RBA appears to have introduced a bit more persistence into the OCR and seems to have deliberately avoided any expansionary overshooting following a contractionary shock. In the late inflation targeting period, the RBA further increased the persistence of the OCR, but may have allowed some expansionary offset at long horizons, although it is not significant.

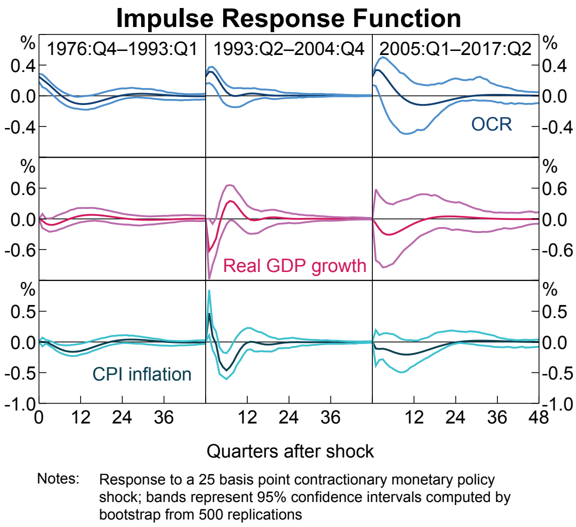


Figure 15: Impulse responses functions for OCR, real GDP growth, and CPI inflation in pre, early, and late inflation targeting periods

In terms of the effects of a contractionary monetary policy, the second and third rows of Figure 15 display the subsample responses of real GDP growth and CPI inflation, respectively. In the pre inflation targeting period, the contractionary shock always decreases real GDP growth at short horizons, but the lower OCR at longer horizons seems to have stimulative effects. In the early inflation targeting period, the response of real GDP is quite volatile, perhaps reflecting a less successful identification of a policy shock for this subsample, as evidenced by a return of a price puzzle in terms of the response of CPI inflation compared to the full sample results or the other subsample results. The strong rebound of real GDP growth could then reflect too quick of a decrease in the policy rate back to zero in the face of an underlying inflationary shock that led to a policy contraction.[17] In the late inflation

[17]The BBE approach to monetary policy shock identification for the FAVAR always risks including contemporaneous shocks to the economy that the RBA immediately responds to in the identified monetary

targeting period with the policy framework well established, the more persistent contraction of monetary policy has more amplified and predicted effects on real GDP growth and CPI inflation, including no price puzzle.

Using the estimated impulse responses for a monetary policy shock, we examine implied sacrifice ratios for the Australian economy by calculating the accumulated response of real GDP relative to the response of CPI inflation. Figure 16 plots these ratios at the 1-2 year horizon for the different subsamples and the full sample as a benchmark. It appears that the sacrifice ratio initially fell with the introduction of inflation targeting, consistent with the idea that a credible nominal anchor can allow inflation expectations to adjust more quickly. However, the sacrifice ratio rose considerably after the mid 2000s, perhaps corresponding to a flattening of the Phillips Curve (also see Gillitzer and Simon 2015). Of course, if this flattening is due to an anchoring of inflation expectations, then a high sacrifice ratio is not a problem in and of itself as the RBA should not need to undertake a large disinflation in the first place.

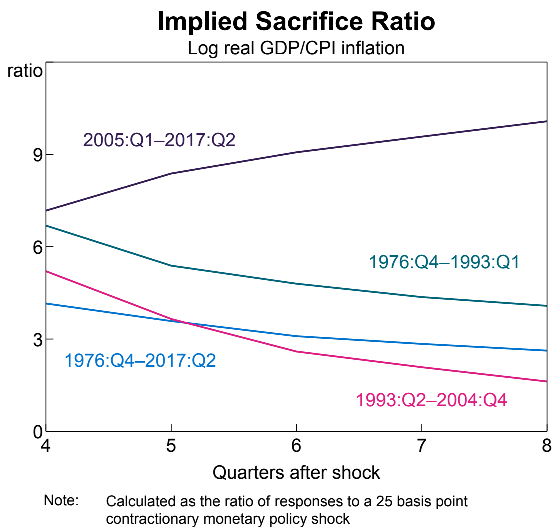


Figure 16: Implied sacrifice ratios

policy shock. In particular, the identified shock is effectively the forecast error for the policy rate from the VAR with the policy rate and the two rotated factors (see the appendix for details). To the extent that most of the forecast error reflects a surprise exogenous change in the policy rate, this approach works well. However, it may be that there were some relatively large endogenous surprise changes in the policy rate during the early inflation targeting period that led to a return of the price puzzle.

5 Conclusion

Factor model analysis provides a useful way to investigate the effects of inflation targeting and the transmission of monetary policy shocks for the Australian economy. Notably, inflation targeting has not just stabilized the level of inflation, but it has also reduced the volatility of common movements in macroeconomic variables. A drop in the implied signal-to-noise ratios for macroeconomic data given a larger decline in common volatility relative to idiosyncratic volatilities implies an increased benefit of considering common factors instead of focusing only on individual noisy series such as CPI inflation. Our FAVAR estimates suggest that monetary policy shocks have become more persistent and their effects amplified, while sacrifice ratios and the implied slope of the Phillips Curve have also changed over time.

The flexibility of factor modelling allows us to propose a number of possible extensions to the our analysis. We plan in the future to consider 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 will allow us to determine if there is any recurring state dependence in the effects of monetary policy shocks or other identified shocks (e.g., foreign shocks) related to business cycle regimes or if there are other slower moving changes. We also plan to utilize recently developed methods for jointly estimating level and volatility factors and their interaction (Koopman et al. 2018). This will allow us to examine the role of "uncertainty" in driving the Australian economic conditions in a data rich environment.

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Appendix

A Australian Macroeconomic Dataset

Table A1: Full list of variables

Number	Name	Category	Transformation	Slow Variable
1	Gross Domestic Product (GDP)	Expenditure	$\log(\Delta x_t)$	Yes
2	Non-Farm GDP	Expenditure	$\log(\Delta x_t)$	Yes
3	GDP Per Capita	Expenditure	$\log(\Delta x_t)$	Yes
4	Gross Domestic Income	Income	$\log(\Delta x_t)$	Yes
5	Public Final Demand	Expenditure	$\log(\Delta x_t)$	Yes
6	Private Final Demand	Expenditure	$\log(\Delta x_t)$	Yes
7	Private Gross Fixed Capital Formation (GFCF)	Expenditure	$\log(\Delta x_t)$	Yes
8	Gross Operating Surplus: Financial Corporations	Income	$\log(\Delta x_t)$	Yes
9	Gross Operating Surplus: Private Non-financial	Income	$\log(\Delta x_t)$	Yes
10	Gross Operating Surplus: Public Non-financial	Income	$\log(\Delta x_t)$	Yes
11	Household Disposable Income	Income	$\log(\Delta x_t)$	Yes
12	Household Consumption (HC)	Expenditure	$\log(\Delta x_t)$	Yes
13	HC: Cigarettes and Tobacco	Expenditure	$\log(\Delta x_t)$	Yes
14	HC: Alcohol Beverages	Expenditure	$\log(\Delta x_t)$	Yes
15	HC: Clothing and Footwear	Expenditure	$\log(\Delta x_t)$	Yes
16	HC: Food	Expenditure	$\log(\Delta x_t)$	Yes
17	HC: Household Equipment	Expenditure	$\log(\Delta x_t)$	Yes
18	HC: Purchase of Vehicles	Expenditure	$\log(\Delta x_t)$	Yes
19	HC: Rent and Other Dwelling Services	Expenditure	$\log(\Delta x_t)$	Yes
20	HC: Hotels, Cafes and Restaurants	Expenditure	$\log(\Delta x_t)$	Yes
21	HC: Transport Services	Expenditure	$\log(\Delta x_t)$	Yes
22	Private GFCF: Dwellings: Alterations and Additions	Expenditure	$\log(\Delta x_t)$	Yes
23	Private GFCF: Dwellings: New and Used	Expenditure	$\log(\Delta x_t)$	Yes
24	Private Non-farm Inventories to Total Sales	Expenditure	Δx_t	Yes
25	Changes in Inventories	Expenditure	x_t	Yes
26	Agriculture, Forestry and Fishing	Production	$\log(\Delta x_t)$	Yes
27	Mining and Exploration	Production	$\log(\Delta x_t)$	Yes
28	Manufacturing	Production	$\log(\Delta x_t)$	Yes
29	Electricity, Gas, and Water Services	Production	$\log(\Delta x_t)$	Yes
30	Construction	Production	$\log(\Delta x_t)$	Yes
31	Wholesale Trade	Production	$\log(\Delta x_t)$	Yes
32	Retail Trade	Production	$\log(\Delta x_t)$	Yes
33	Accommodation and Food Services	Production	$\log(\Delta x_t)$	Yes
34	Transportation	Production	$\log(\Delta x_t)$	Yes
35	Info Media and Telecommunication	Production	$\log(\Delta x_t)$	Yes
36	Financial and Insurance Services	Production	$\log(\Delta x_t)$	Yes
37	Rental, Hiring and Real Estate Services	Production	$\log(\Delta x_t)$	Yes
38	Professional, Scientific, and Technical Services	Production	$\log(\Delta x_t)$	Yes
39	Administration and Support Services	Production	$\log(\Delta x_t)$	Yes
40	Public Administration and Safety	Production	$\log(\Delta x_t)$	Yes
41	Education and Training	Production	$\log(\Delta x_t)$	Yes
42	Healthcare and Social Assistance	Production	$\log(\Delta x_t)$	Yes
43	Arts and Recreation Services	Production	$\log(\Delta x_t)$	Yes
44	Other Services	Production	$\log(\Delta x_t)$	Yes
45	Full Time Employment	Employment	$\log(\Delta x_t)$	Yes
46	Part Time Employment	Employment	$\log(\Delta x_t)$	Yes
47	Total Employment	Employment	$\log(\Delta x_t)$	Yes
48	Unemployment Rate	Employment	Δx_t	Yes
49	Labour Productivity	Employment	$\log(\Delta x_t)$	Yes

Continued on next page

Table 5 – continued from previous page

Number	Name	Category	Transformation	Slow Variable
50	Real Unit Labour Costs	Employment	$\log(\Delta x_t)$	Yes
51	Average Weekly Earnings	Employment	$\log(\Delta x_t)$	Yes
52	Average Weekly Hours Worked	Employment	$\log(\Delta x_t)$	Yes
53	Capacity Utilisation (net balance)	Surveys	x_t	No
54	General Business Situation (next 6 months net balance)	Surveys	x_t	No
55	Output Actual (change in past 3 months net balance)	Surveys	x_t	No
56	Output Expected (change in next 3 months net balance)	Surveys	x_t	No
57	Commencements: Total New Houses and Flats ex. Conversion	Building & Capex	$\log(\Delta x_t)$	No
58	Completed: Total New Houses and Flats ex. Conversion	Building & Capex	$\log(\Delta x_t)$	Yes
59	Approvals: Private New Houses and Flats	Building & Capex	$\log(\Delta x_t)$	No
60	Approvals: Govt New Houses and Flats	Building & Capex	$\log(\Delta x_t)$	No
61	Approvals: Total New Houses and Flats	Building & Capex	$\log(\Delta x_t)$	No
62	Current Account (per cent of GDP)	Overseas Transactions	Δx_t	Yes
63	Services Imports	Overseas Transactions	$\log(\Delta x_t)$	Yes
64	Services Exports	Overseas Transactions	$\log(\Delta x_t)$	Yes
65	Goods Debits	Overseas Transactions	$\log(\Delta x_t)$	Yes
66	Goods Credits	Overseas Transactions	$\log(\Delta x_t)$	Yes
67	Consumer Pric Index (CPI): All Groups	Prices	$\log(\Delta x_t)$	Yes
68	CPI: Food and Non-Alcoholic Beverages	Prices	$\log(\Delta x_t)$	Yes
69	CPI: Alcohol and Tobacco	Prices	$\log(\Delta x_t)$	Yes
70	CPI: Clothing and Footwear	Prices	$\log(\Delta x_t)$	Yes
71	CPI: Housing	Prices	$\log(\Delta x_t)$	Yes
72	CPI: Household Equipment and Services	Prices	$\log(\Delta x_t)$	Yes
73	CPI: Transportation	Prices	$\log(\Delta x_t)$	Yes
74	CPI: Communication	Prices	$\log(\Delta x_t)$	Yes
75	CPI: Goods Component	Prices	$\log(\Delta x_t)$	Yes
76	CPI: Services Component	Prices	$\log(\Delta x_t)$	Yes
77	ABS Established House prices	Prices	$\log(\Delta x_t)$	Yes
78	Oil Prices	Prices	$\log(\Delta x_t)$	No
79	GDP Price Deflator	Prices	$\log(\Delta x_t)$	Yes
80	Household Final Consumption Expenditure Price Deflator	Prices	$\log(\Delta x_t)$	Yes
81	Private GFCF Price Deflator	Prices	$\log(\Delta x_t)$	Yes
82	Domestic Final Demand (DFD) Price Deflator	Prices	$\log(\Delta x_t)$	Yes
83	Export Price Index: Goods and Services Credits	Prices	$\log(\Delta x_t)$	Yes
84	Import Price Index: Goods and Services Debits	Prices	$\log(\Delta x_t)$	Yes
85	Terms of Trade	Prices	$\log(\Delta x_t)$	Yes
86	Index of Commodity Prices (ICP)	Prices	$\log(\Delta x_t)$	No
87	Money: M1	Money & Credit	$\log(\Delta x_t)$	No
88	Money: M3	Money & Credit	$\log(\Delta x_t)$	No
89	Money: Broad Money	Money & Credit	$\log(\Delta x_t)$	No
90	Credit: Total	Money & Credit	$\log(\Delta x_t)$	No
91	Credit: Other Personal	Money & Credit	$\log(\Delta x_t)$	No
92	Credit: Business	Money & Credit	$\log(\Delta x_t)$	No
93	Overnight Cash Rate (OCR)	Interest Rates	Δx_t	No
94	Real Overnight Cash Rate	Interest Rates	Δx_t	No
95	3 Month Bank Bill	Interest Rates	Δx_t	No
96	5 Year Australia Government Security (AGS)	Interest Rates	Δx_t	No
97	10 Year Australia Government Security (AGS)	Interest Rates	Δx_t	No
98	3 Month Bank Bill spread to OCR	Interest Rates	x_t	No
99	5 Year AGS spread to OCR	Interest Rates	x_t	No
100	10 Year AGS spread to OCR	Interest Rates	x_t	No
101	Share Price Index	Misc	$\log(\Delta x_t)$	No
102	Real Trade Weighted Exchange Rate Index (TWI)	Misc	$\log(\Delta x_t)$	No
103	Southern Oscillation Index (SOI)	Misc	x_t	No
104	Consumer Sentiment Index	Surveys	x_t	No

Notes: Data are seasonally adjusted when available. 'Transformation' refers to the method used to transform the respective series before extracting the factors. 'Slow Variable' refers to whether the respective series is used to extract 'slow moving' factors as part of the procedure when estimating the FAVAR model.

B Quasi Maximum Likelihood Estimation

Following Doz et al. (2012), we consider a dynamic factor model estimated by quasi maximum likelihood estimation (QMLE). The estimation is 'quasi' in the sense that the underlying model is misspecified. The source of misspecification relates to omitted cross-sectional correlation of the idiosyncratic components. 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-section dimension N. The state-space form of the QMLE dynamic factor model is given as follows:

$$
\begin{aligned}
Y_t &= \Lambda F_t + \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0, R), \\
F_t &= \Phi F_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, Q).
\end{aligned}
$$

The parameter matrices of the measurement and state equations have the following structure:

$$
Y_t = \begin{pmatrix} \Lambda & 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} F_t \\ F_{t-1} \\ \vdots \\ F_{t-p+2} \\ F_{t-p+1} \end{pmatrix} + \epsilon_t,
$$

$$
\begin{pmatrix} F_t \\ F_{t-1} \\ \vdots \\ F_{t-p+2} \\ F_{t-p+1} \end{pmatrix} = \begin{pmatrix} \Phi_1 & \Phi_2 & \cdots & \Phi_{p-1} & \Phi_p \\ I_r & 0_r & \cdots & 0_r & 0_r \\ \vdots & \vdots & & \vdots & \vdots \\ 0_r & 0_r & \cdots & 0_r & 0_r \\ 0_r & 0_r & \cdots & I_r & 0_r \end{pmatrix} \begin{pmatrix} F_{t-1} \\ F_{t-2} \\ \vdots \\ F_{t-p+1} \\ F_{t-p} \end{pmatrix} + \begin{pmatrix} I_r \\ 0_r \\ \vdots \\ 0_r \\ 0_r \end{pmatrix} \eta_t,
$$

where I_r is an r-dimensional identity matrix and 0_r is an r-dimensional matrix of zeros. The covariance matrix of ϵ_t in the measurement equation, which is the same as equation (1), is given by R with dimension $N \times N$ and is restricted to be a diagonal matrix. In the state equation, the covariance matrix of η_t corresponds to the upper $r \times r$ submatrix of the rp-dimensional square matrix Q with the remaining elements set to zero. We set p to be 1 based on the Schwarz information criterion (SIC).

The QML estimator is implemented using the Kalman filter-smoother and the EM algorithm. To do this we initialise the Kalman filter-smoother recursions using the first r PC-based estimates of the factors and OLS estimates of the parameters Λ, $\Phi(L)$, R, and Q, treating the PC factors as the true common factors. This represents the 'expectation' step and provides a new estimate of the common factors given the estimated parameters. Based on the updated estimate of the factors, we compute new parameter estimates via OLS (this is the 'maximisation step'). These two steps are repeated until the algorithm converges. We set convergence criterion to be when c_m is less than 10^{-6}, with c_m given by:

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

where θ is a vector of the model parameters and $m = 1, \ldots, M$ is the number of evaluations needed to achieve convergence up to a maximum M set by the researcher. We set $M = 1000$, but the number of evaluations needed in all cases considered was much less than 100. $\mathcal{L}\left(Y; \hat{\theta}\right)$ is the log-likelihood function given as:

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

with the initial state $F_0 = 0_{rp}$ and initial state variance $P_0 = \left(I_{rp^2} - \Phi \otimes \Phi\right)^{-1} \mathrm{vec}(Q)$. See Ghahramani and Hinton (1996) for more details.

A convenient feature of this specification is that the computational complexity of the Kalman filter-smoother depends only on the number of states, which in our case corresponds to the number of factors r, and is independent of the size of the cross section N.

Note, while the EM algorithm will converge, it is not guaranteed to find the global maximum and can converge to a local maximum. However, the chance of this occurring can be offset by starting the algorithm, as we do, with the PCA estimates which are consistent for large cross sections.

The main reason we use this estimation method relates to its potential to improve efficiency of the estimates of the common factors. This comes from explicitly accounting for factor dynamics. Doz et al. (2012) show the efficiency improvements are relevant when there are more common factors to estimate. Other desirable features of this method (which we do not explore in our work) relate to structural analysis by allowing the researcher to impose restrictions on the factor loadings to extract shocks. Furthermore, the method is capable of handling either missing or mixed frequency data.

C FAVAR Estimation

Here we describe the FAVAR model estimation in detail. Let R_t be the Official Cash Rate (OCR). Suppose that additional economic information can be summarised by a $k \times 1$ vector of unobserved factors F_t, where k is "small" and is not necessarily equal to r as determined via some formal selection criteria. We can think of the unobserved factors as possibly capturing variation in 'economic activity' or 'price pressures' that may not be readily proxied by any particular individual observed variable, but are important in a wide range of economic data series.

Assume the joint dynamics of F_t and R_t are given by the following equation:

$$\begin{pmatrix} F_t \\ R_t \end{pmatrix} = \Phi(L) \begin{pmatrix} F_{t-1} \\ R_{t-1} \end{pmatrix} + \epsilon_t,$$

where $\Phi(L)$ is a conformable lag polynomial of finite order p. We set $p = 2$ in our case based on SIC. We then assume that what BBE call 'informational' time series Y_t are related to the unobserved factors F_t and observed R_t by the equation:

$$Y_t = \Lambda_F F_t + \Lambda_R R_t + e_t,$$

where Λ_F is an $N \times k$ matrix of common factor loadings, Λ_R is an $N \times 1$ vector of R_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.

We consider only one approach to estimating the FAVAR (BBE consider two, one via PCA and the other via Bayesian estimation). We use their two-step method based on the PCA estimator, but we replace this with the QMLE estimates of the factors. This is not new as Bernanke and Boivin (2003) did something similar using a mixed frequency panel for the U.S. economy. Denote the estimated common factors of Y_t by $\hat{C}(F_t, R_t)$. Because $\hat{C}(F_t, R_t)$ corresponds to an arbitrary linear combination of its arguments, obtaining $\hat{F}_t$ involves determining the part of $\hat{C}(F_t, R_t)$ that is not spanned by R_t.

Because R_t is not explicitly imposed as a common component in the first estimation step, any of the linear combinations underlying $\hat{C}(F_t, R_t)$ could involve R_t. BBE argue that it would not be valid to simply estimate a VAR based on $\hat{C}(F_t, R_t)$ and identify the policy shock recursively. Instead, they argue that the direct dependence of the common factors of Y_t on R_t must be removed first.

If linear combinations implicit in $\hat{C}(F_t, R_t)$ were known, this would involve subtracting R_t times the associated coefficient from each of the elements of $\hat{C}(F_t, R_t)$. However, because they are unknown, BBE propose to estimate the coefficients through a multiple regression of the form:

$$\hat{C}(F_t, R_t) = \beta_{C^*}\hat{C}^*(F_t) + \beta_R R_t + \nu_t,$$

where $\hat{C}^*(F_t)$ is an estimate of all the common components other than R_t. BBE suggest one way to obtain $\hat{C}^*(F_t)$ is to extract factors from a subset of slow-moving variables, which by assumption are not affected contemporaneously by R_t. Then $\hat{F}_t$ is constructed as $\hat{C}(F_t) - \hat{\beta}_R R_t$ and a VAR in $\hat{F}_t$ and R_t is estimated using OLS and identified recursively.

Note that the key assumption is that most of the forecast error for R_t reflects monetary policy shocks, not an endogenous response to economic conditions. Finally, because this second step involves the presence of "generated regressors", we use the bootstrap and 500 replications to compute confidence bands for the impulse response functions displayed in Section 4.