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The Sticky Information Phillips Curve: Evidence for Australia

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Abstract

The Sticky Information Phillips Curve (SIPC) provides a theoretically appealing alternative to the sticky-price New-Keynesian Phillips curve (NKPC). This paper assesses the empirical performance of the SIPC for Australia. There is only weak evidence in favour of the SIPC over the low-inflation period. Parameter estimates are sensitive to inflation measures and sample periods, and are theoretically inconsistent for several specifications. The apparent poor performance of the SIPC in part reflects the fact that inflation has become difficult to model since the introduction of inflation targeting. Over sample periods including the early 1990s disinflation, the SIPC appears to fit the data better.

JEL Classification Numbers: E3, E31

Keywords: sticky information, Phillips curve, inflation, Australia

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1. Introduction

Modelling inflation is a core task for inflation-targeting central banks. Like other central banks, the Reserve Bank of Australia (RBA) evaluates and uses a variety of models for inflation. The set of models differ substantially in their style and purpose. At one end of the spectrum are reduced-form single or multi-equation models. These models typically impose few parameter restrictions and are used for forecasting. At the other end of the spectrum are microfounded dynamic stochastic general equilibrium (DSGE) models, which are mostly used for scenario analysis. In between these two extremes are more microfounded single-equation models. While reduced-form models typically provide the best forecasting performance, their lack of structure makes them less suited to policy analysis.

The New-Keynesian Phillips curve (NKPC) has become the canonical microfounded model of inflation in the academic community, being widely used in theoretical work. In its pure or hybrid variants, it is also a central element of DSGE models used by most central banks (e.g. Smets and Wouters 2007). Like all models, its usefulness for policy analysis depends on the assumptions underpinning the model. The key assumption of the New-Keynesian sticky-price model is a restriction on the frequency with which firms can change their prices. This assumption is consistent with the infrequency with which retail prices change for many goods and services. But a large literature highlights the inability of the basic sticky-price model to match the inertial behaviour of inflation, and the delayed and gradual response of inflation to monetary policy shocks.[1] Other counterfactual predictions of the sticky-price model are the possibilities of costless disinflations and disinflationary booms (Ball 1994).

The New-Keynesian model has trouble matching the inertial behaviour of inflation because it implies that, while the price level is sticky, the inflation rate can jump.

1 See Mankiw (2001), and the references therein, for a critique of the sticky-price model, and Christiano, Eichenbaum and Evans (1999) for evidence on the response of inflation to monetary policy shocks.

The model assumes that a randomly chosen subset of firms are able to change their price each period. Firms anticipate the likelihood of being stuck at their reset price for several periods, making inflation highly forward-looking and responsive to macroeconomic news. The peak response of inflation to a monetary policy shock in the canonical sticky-price NKPC is immediate, and thus the NKPC cannot match the persistence of inflation, or generate the output-inflation correlations evident in the data (Fuhrer and Moore 1995; Mankiw 2001).

As an alternative to the sticky-price model, Mankiw and Reis (2002) propose a Sticky Information Phillips Curve (SIPC). Building on Lucas (1973) and Carroll (2003), the SIPC assumes that macroeconomic news disseminates slowly throughout the population. Only some firms receive updated information about output and inflation each period, with the remainder continuing to set prices based on outdated information. Firms are always free to change prices, but only some firms change prices based on updated information. Slow dissemination of macroeconomic news generates inertial inflation dynamics when there is strategic complementarity in price setting. Firms acquiring new information take into account that other firms remain uninformed, and incorporate macroeconomic news into pricing decisions gradually, as the share of informed firms rises. In contrast, inflation in the NKPC model is entirely forward looking.

This paper provides the first estimates of the SIPC for Australian data. The model is tested using a range of inflation measures, forecast series and sample periods. Overall, the estimation results provide only weak support for the SIPC, particularly over the low-inflation period. The estimated degree of information rigidity differs substantially across sample periods and inflation measures. For consumer price index (CPI) inflation over the 1995–2013 period, the estimated degree of information rigidity using Consensus Economics and official RBA forecasts is theoretically inconsistent, indicating rejection of the model. But for underlying inflation, the estimated degree of information rigidity is theoretically consistent, with estimates implying that firms on average update their information sets each 6–8 quarters. Including data prior to the introduction of inflation targeting in the estimation sample improves the performance of the SIPC, but there is still substantial parameter instability across specifications.

Some of the estimated parameter instability can be explained by differences in inflation inertia across sample periods and inflation measures. A high degree of information rigidity puts substantial weight on old forecasts of current inflation, generating sluggish inflation dynamics. This is a key objective of the sticky-information model, but it is inconsistent with the behaviour of CPI inflation over the low-inflation period. Conversely, the variability of the inertial trend component of inflation was relatively high prior to the introduction of inflation targeting (IT), and the estimated degree of information rigidity is, in general, substantial. Reflecting this, the fit of the SIPC is generally better over sample periods including the pre-IT regime.

Reflecting the weak relationship between inflation and the output gap, particularly over the low-inflation period, the estimated degree of real rigidity is imprecisely estimated. The relationship between the nominal and real side of the model depends non-linearly on the degree of information rigidity, and the degree of real rigidity is most imprecisely estimated when the degree of information rigidity is high.

An important theoretical feature of the SIPC is its ability to generate costly disinflations. Despite this, the SIPC does not perform well during the early 1990s disinflation, except with very low levels of information rigidity. This is because the SIPC places weight on dated real-time long-horizon inflation forecasts, which substantially overpredicted inflation during the early 1990s disinflation. Coibion (2010) labels this the *real-time forecast error effect*. In contrast, the forward-looking NKPC model better predicts the disinflation because it places no weight on dated long-horizon inflation forecasts.

These findings are broadly similar to Coibion (2010) for US data, who finds that the SIPC generates excessively inertial inflation dynamics, and can be strongly rejected in favour of the NKPC. Kahn and Zhu (2006) present more favourable evidence for the SIPC using US data, estimating that firms update their information sets each 3–7 quarters. Döpke *et al* (2008) provide similarly favourable evidence for France, Germany and the United Kingdom, finding that firms update their information sets once a year. However, both Kahn and Zhu (2006) and Döpke *et al* (2008) impose the degree of real rigidity, rather than estimating the parameter. I find that imposing the degree of real rigidity can have a substantial effect on the estimated degree of information rigidity. Kiley (2007) and Koronek (2008) both reject the SIPC in favour of the NKPC using US data, although Kiley finds that a hybrid NKPC model fits the data best, and suggests that the importance of lagged inflation may capture information rigidity. However, both Kiley (2007) and Koronek (2008) use in-sample forecasts, which can be misleading, particularly when there are mean-shifts in inflation. I use only real-time or quasi real-time forecasts in assessing the empirical performance of the SIPC. More broadly, this paper's findings add to a body of work modelling Australian inflation. Norman and Richards (2010) provide a recent critical evaluation of structural and reduced-form single-equation inflation models for Australia. Their main finding is that an expectations-augmented standard Phillips curve and mark-up models outperform the NKPC in terms of in-sample fit and significance of the model coefficients. Given that I find the fit of the SIPC to be generally no better than the NKPC, the ranking of models in Norman and Richards is unchanged.

The remainder of the paper proceeds as follows: Section 2 describes the SIPC and NKPC models, and discusses estimation issues; Section 3 describes the forecasts used; and Section 4 presents the estimation results. Some concluding thoughts are offered in Section 5.

2. Model and Estimation

2.1 Sticky Information Phillips Curve

The log of a firm's desired price p_t^*, relative to the log aggregate price level p_t, is proportional to the output gap:

$$p_t^* = p_t + \alpha x_t, \tag{1}$$

where x_t is the output gap and α is the degree of real rigidity (the elasticity of a firm's desired relative price with respect to the output gap). The smaller is the parameter α, the greater is the degree of strategic complementarity between firms, reducing the sensitivity of firms' desired price to the output gap.[2] Each period, a randomly chosen fraction $(1-\lambda)$ of firms receive updated inflation and output gap forecasts for each quarter in the future.[3] The remaining λ share of firms do not

2 This condition can be derived from a firm's profit maximisation condition. See, for example, Blanchard and Kiyotaki (1987).

3 The SIPC assumes that λ is a structural parameter. See Reis (2006) for a model that microfounds the optimal degree of inattention.

acquire new information, and continue to set prices based on outdated information. The assumption that a fraction of firms continue to work with outdated information each period enables the SIPC to generate inertial inflation dynamics: only prices set by firms acquiring new information will reflect shocks to inflation and output gap forecasts. Combining Equation (1) with the assumption of a state-independent probability of acquiring new forecasts yields the SIPC:

$$\pi_t = \left[\frac{1-\lambda}{\lambda}\right]\alpha x_t + (1-\lambda)\sum_{j=0}^{\infty}\lambda^j E_{t-j-1}\left[\pi_t + \alpha\Delta x_t\right], \tag{2}$$

where π_t is the quarterly inflation rate and $\Delta x_t = x_t - x_{t-1}$ is the contemporaneous change in the output gap. Equation (2) indicates that current inflation in part reflects past expectations of current inflation. Mankiw and Reis (2002) motivate the SIPC by relation to a contracting model, in which prices reflect expectations at the time contracts were set. When firms acquire new information, they are assumed to receive rational expectations forecasts. With this assumption, the model resembles Carroll's (2003) epidemic model of information diffusion, in which a random subset of consumers come into contact with professional forecasters each period.

Reflecting the fact that Australia is a small open economy, the baseline closed-economy SIPC is augmented with an import price term, allowing firms' desired price to depend on both the output gap and the cost of imported goods and services. With import prices, Equation (1) generalises to $p_t^* = p_t + \alpha x_t + \xi\hat{\pi}_t^m$, where $\hat{\pi}_t^m \equiv p_t^m - p_t$ is the detrended real log goods and services import price deflator (adjusted for tariff changes). The corresponding open-economy SIPC is given by:

$$\pi_t = \left[\frac{1-\lambda}{\lambda}\right]\left(\alpha x_t + \xi\hat{\pi}_t^m\right) + (1-\lambda)\sum_{j=0}^{\infty}\lambda^j E_{t-j-1}\left[\pi_t + \alpha\Delta x_t + \xi\Delta\hat{\pi}_t^m\right]. \tag{3}$$

Estimation of the SIPC requires truncating the infinite order lag of expectations and adding an error term ε_t:

$$\pi_t = c + \left[\frac{1-\lambda}{\lambda}\right]\alpha x_t + (1-\lambda)\sum_{j=0}^{J}\lambda^j E_{t-j-1}\left[\pi_t + \alpha\Delta x_t\right] + \gamma\hat{\pi}_t^m + \varepsilon_t. \tag{4}$$

A constant term c has also been added. Because import price forecasts are unavailable, the terms $E_{t-j-1}\left[\xi\Delta\hat{\pi}_t^m\right]$ in Equation (3) are omitted; with this simplification, the import price term can be separated from the information rigidity term, noting that $\gamma = (1-\lambda/\lambda)\,\xi$.

In general, the output gap term x_t in the SIPC will be correlated with shocks to inflation, in which case ordinary least squares will provide inconsistent estimates of the model parameters. If the error term is iid, any variables known at time $t-1$ are valid instruments. But truncating the infinite order lag of expectations is likely to violate this orthogonality condition. The error term ε_t in Equation (4) consists of all forecasts dated $t-J-2$ and earlier,

$$\varepsilon_t = (1-\lambda)\sum_{j=J+1}^{\infty}\lambda^j E_{t-j-1}\left[\pi_t + \alpha\Delta x_t\right] + u_t, \tag{5}$$

plus an idiosyncratic error term u_t. In general, forecasts dated $t-J-2$ and earlier will be correlated with instruments dated $t-1$ and earlier. But provided the truncation point is sufficiently long, and λ is not too large, any inconsistency in the parameter estimates is likely to be small. Forecasts dated $t-J-2$ and earlier receive weight no greater than $(1-\lambda)\lambda^{J+1}$, and thus induce a relatively weak correlation between ε_t and candidate instruments dated $t-1$ and earlier. Coibion (2010) uses Monte Carlo simulation, and data at a quarterly frequency, to show that for $\lambda = 0.75$ (firms update their information set on average once per year), consistent estimation can be achieved with truncation of expectations beyond one year. The set of instruments used to estimate Equation (4) includes the full set of forecasts and the first lag of the output gap. The output gap is the only endogenous variable, and because it is highly correlated with the lagged output gap used as an instrument, the SIPC parameter estimates do not suffer from bias caused by weak instruments.

2.2 New-Keynesian Phillips Curve

For comparison with the SIPC, a NKPC is also estimated. The assumptions underlying the NKPC flip those of the SIPC. The NKPC assumes that firms obtain rational expectations forecasts in each period, but face a restriction on their ability to reset prices: with state-independent probability $(1-\theta)$, a firm is able to reset its price each period. Firms' desired price in each period is given by Equation (1), the same as in the SIPC, but because firms are unable to adjust their price with probability θ in each period, their chosen price when they are free to adjust is a weighted average of their desired price over the expected duration that its price is fixed. This price-setting behaviour implies the following open economy NKPC:

$$\pi_t = \rho x_t + E_t\left[\pi_{t+1}\right] + \gamma \hat{\pi}_t^m, \tag{6}$$

where $\rho = \alpha\kappa$, with $\kappa = (1-\theta)^2/\theta$ the elasticity of inflation with respect to real marginal cost and, as in the SIPC, α the degree of real rigidity. Often, the driving variable in the NKPC is real marginal cost, rather than the output gap. The output gap is used here for consistency with the SIPC, and because of the relative unreliability of marginal cost estimates.

Import prices are a component of firms' marginal cost, and the sticky-price assumption underlying the NKPC means that changes in import prices are incorporated into consumer prices each period by only a $(1-\theta)$ subset of firms. This implies that the coefficient γ on the import price term is equal to κ multiplied by the share of marginal cost accounted for by import prices: $\gamma = \kappa s$. For comparability with the SIPC, this restriction is not imposed.

The NKPC is augmented with an error term and a constant,

$$\pi_t = c + \rho x_t + \beta E_t\left[\pi_{t+1}\right] + \gamma \hat{\pi}_t^m + \varepsilon_t. \tag{7}$$

The key feature of the NKPC model is the presence of forward-looking inflation expectations, compared to lagged expectations in the SIPC. The NKPC is estimated using the same set of professional and econometric forecasts used to estimate the SIPC. The instrument set consists of the first lag of the output gap, and the time $t-1$ forecast of inflation at time $t+1$. The most common estimation method for the NKPC replaces expected inflation with its realisation and seeks appropriate instruments. Any pre-determined variable is a valid instrument, but weak identification is a common problem. The use of survey forecasts mitigates this problem: survey forecasts exhibit high serial correlation, in which case $E_{t-1}\left[\pi_{t+1}\right]$ is a strong instrument for $E_t\left[\pi_{t+1}\right]$. But the use of survey forecasts to estimate the NKPC introduces theoretical complications. The NKPC is derived assuming rational expectations, but expectations are non-rational under the SIPC assumptions, because each period firms retain dated forecasts with probability λ. Nonetheless, Mavroeidis, Plagborg-Møller and Stock (2014, p 135) argue that '[w]hile the proper microfoundations for price setting under nonrational expectation formation are lacking, the survey forecasts specification may still be taken as a primitive ...'. Of particular importance here, the use of forecasts facilitates comparison between the estimated SIPC and NKPC specifications.

Inflation in the NKPC specified by Equation (6) is entirely forward-looking, unlike hybrid specifications that include lagged inflation as an explanatory variable (see, for example, Galí and Gertler (1999) and Galí, Gertler and López-Salido (2005)). The SIPC provides a microfoundation for the inertial behaviour of inflation that the hybrid specification seeks to match in a reduced-form way. The SIPC is compared against a forward-looking rather than hybrid NKPC in order to provide a clear contrast between the alternative sticky-price and sticky-information models of price setting.

3. Forecasts

3.1 Availability and Construction

Estimation of the SIPC requires knowledge of the expected path of inflation and the output gap for each vintage of expectations. Since the early 1990s, Consensus Economics has compiled inflation and GDP growth forecasts based on a survey of professional forecasters.[4] The SIPC requires estimates of changes in the output gap rather than GDP growth but, if we assume that variation in GDP growth is much larger than variation in potential output at short horizons, GDP growth forecasts will provide a suitable proxy.

Official RBA forecasts for CPI inflation, underlying inflation and GDP growth provide an alternative source of expectations data. The RBA has published forecasts of inflation and GDP growth for some period of time, but the full detailed history of forecasts were not made public until 2012. This means that firms could not have used these detailed forecasts to make pricing decisions over the entire sample period. But if similar forecasts were available to firms in real time, the RBA forecasts may provide a reliable guide to expectations. The differences between RBA and Consensus forecasts of CPI inflation and GDP growth have been relatively minor (see Tulip and Wallace (2012)).

4 Quarterly inflation and GDP growth forecasts can be inferred from the reported year-ended changes.

Unfortunately, availability of Consensus and RBA forecasts before the low-inflation period is limited. This is a significant weakness, because changes in inflation regimes are a key source of identification for the sticky-information model. Furthermore, the Consensus and RBA forecast horizons are sometimes as short as one year, necessitating truncation of the SIPC at four lags. By constructing econometric forecasts, we can proxy real-time inflation and output gap growth expectations before the low-inflation period, and for longer forecast horizons.

Following Stock and Watson (2003), the econometric forecasts are based on an average of bi-variate h-step-ahead projections. Each regression includes a candidate variable that is believed to have forecasting ability for inflation or growth in the output gap, plus lags of the dependent variable. Averaging across each set of bi-variate forecasts produces the central forecasts for inflation and the change in the output gap. The use of combination forecasts guards against structural change and over-fitting in short samples. Stock and Watson (2004) provide evidence that forecast combination methods provide good out-of-sample forecast performance relative to an autoregressive model. Kahn and Zhu (2006) and Coibion (2010) use a similar forecasting procedure in testing the empirical performance of the SIPC for the United States.

Formally, to forecast variable y_t at horizon h, the regression

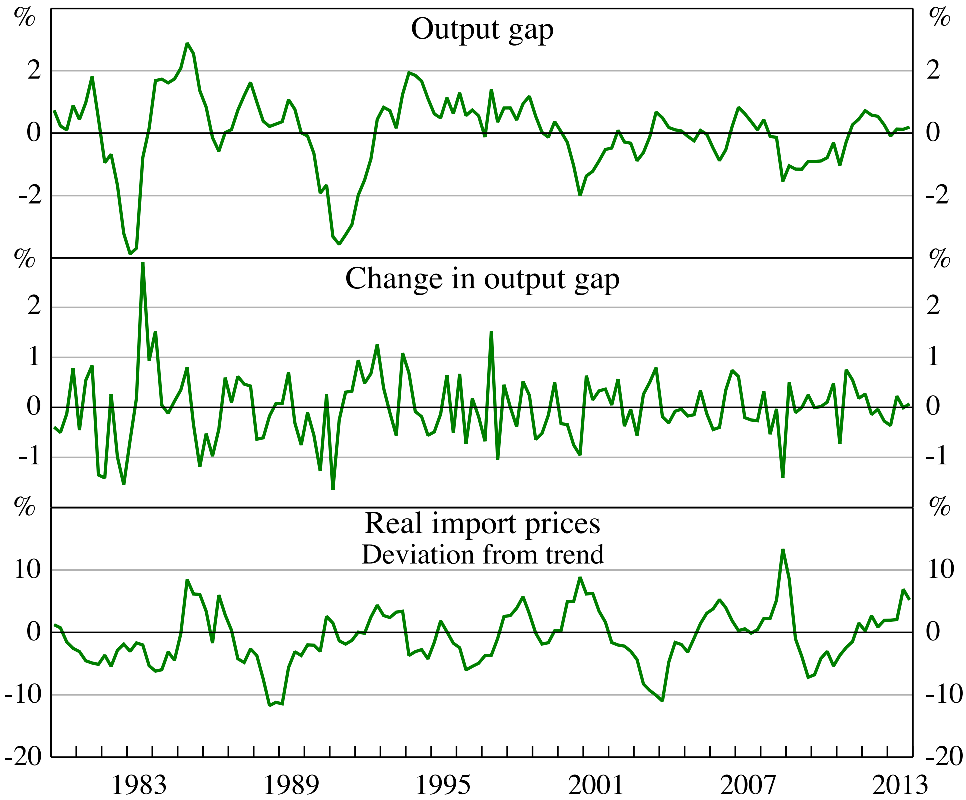
$$y_{t+h} = c + \beta_y(L)\,y_t + \beta_z(L)\,z_t + \varepsilon_{t+h} \tag{8}$$

is run for each forecast series y_{t+h}, candidate predictor z_t, and forecast horizon h. Each regression includes z_t, and up to a maximum of four lags of y_t and z_t, with lag lengths selected using the Akaike information criterion (AIC). The forecast variables are CPI inflation, underlying inflation and the change in the output gap. Rather than forecasting the output gap and then differencing the forecasts, the change in the output gap is forecast directly. The pseudo real-time output gap x_t is estimated from final-vintage GDP data, using a one-sided Hodrick-Prescott (HP) filter.[5] Stock and Watson (1999) report that the one-sided HP-filter produces plausible estimates of the trend component of GDP, without using out-of-sample information. A smoothing parameter of $q = 1\ 600$ is used, as is standard for

5 The one-sided HP-filter models potential output as an unobserved component, assuming innovations to potential output are uncorrelated with the output gap.

quarterly frequency GDP data. The same one-sided HP-filter is used to detrend real import prices. Figure 1 plots the estimated output gap and import price series.

Figure 1: Explanatory Variables



For forecast horizons between one quarter and two years, the first set of quarterly growth forecasts is generated for 1980:Q1, using a ten-year in-sample period to estimate each variant of Equation (8). The estimation period is then moved forward one quarter at a time to 2013:Q4, generating a full set of forecasts for each horizon. The estimation window for Equation (8) is kept at a fixed ten-year length, allowing for structural change in the parameters of each forecasting regression. The use of out-of-sample rather than in-sample forecasts is critical for evaluation of the SIPC. Ideally, out-of-sample forecasts would be constructed using only real-time data. CPI inflation data are not revised and revisions to underlying inflation data occur only as a result of changes in estimated seasonal factors, but for other series data availability requires the use of final vintage data. Table 1 reports the set of variables z_t used to forecast CPI inflation, underlying inflation and the change in the output gap.[6] The selection of these explanatory variables has been guided by Stock and Watson (2003) and Kahn and Zhu (2006). Although few of the variables have a stable forecast relationship over the full sample period, each is likely to contain useful information for forecasting in at least some sub-samples.

Table 1: Econometric Forecasts – Explanatory Variables

	CPI inflation	Underlying inflation	Change in output gap
Activity			
GDP – quarterly percentage change	✓	✓	✓
Output gap	✓	✓	
Capacity utilisation – ACCI-Westpac net balance			✓
Unemployment rate – quarterly change	✓	✓	✓
Prices			
Underlying inflation	✓		✓
Import prices – quarterly percentage change	✓	✓	✓
Oil price (AUD) – quarterly percentage change	✓	✓	✓
Terms of trade – quarterly percentage change	✓	✓	✓
Financial market			
Real trade-weighted index – quarterly percentage change			✓
Share price index – quarterly percentage change	✓	✓	✓
Bank bill interest rate – 90-day	✓	✓	✓
Yield curve slope – 10-year–90-day	✓	✓	✓

3.2 Forecast Performance

Table 2 reports the historical performance of each forecast type relative to an autoregressive benchmark. Each number in the table represents the root mean squared error (RMSE) of the forecast relative to the RMSE of an autoregressive forecast; numbers less than unity indicate improved forecast accuracy relative to an autoregressive forecast. Bootstrapped 95 per cent confidence intervals for the econometric forecasts are reported in square brackets.

6 The underlying inflation measure used is: trimmed mean inflation excluding interest charges and tax changes after 1982, non-seasonally adjusted trimmed mean inflation excluding interest charges and tax changes from 1976–1982, Treasury's underlying inflation from 1971–1976, and CPI inflation before 1971. Import prices have been adjusted to include tariff changes.

Table 2: Forecast Performance – Relative to Autoregressive Forecast

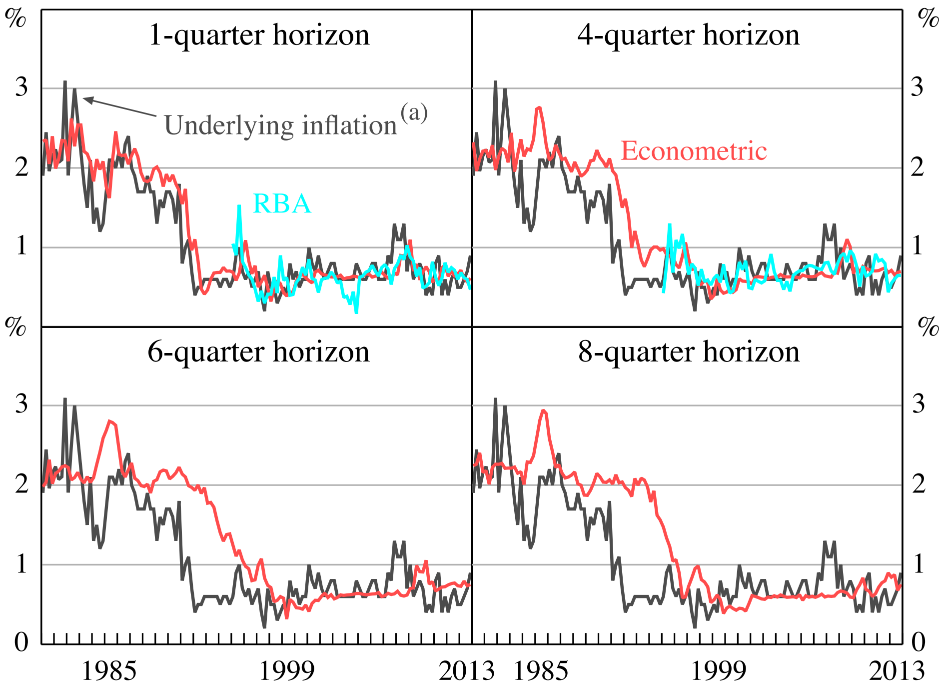
	Sample period	Forecast horizon				
		1-quarter	2-quarter	4-quarter	6-quarter	8-quarter
CPI inflation						
Consensus	1995–2013	0.65	0.72	0.80		
RBA	1995–2011	0.63	0.81	0.84		
Econometric	1995–2013	1.02	1.05	1.05	1.04	1.05
		[0.98, 1.06]	[1.00, 1.09]	[0.99, 1.11]	[0.98, 1.10]	[0.98, 1.12]
	1980–2013	1.00	0.98	0.93	1.01	0.96
		[0.97, 1.04]	[0.95, 1.02]	[0.88,0.97]	[0.96, 1.06]	[0.90, 1.02]
Underlying inflation						
RBA	1995–2011	1.11	0.97	1.06		
Econometric	1995–2013	1.00	0.96	1.03	1.04	0.98
		[0.94, 1.06]	[0.90, 1.03]	[0.95, 1.11]	[0.96, 1.12]	[0.90, 1.06]
	1980–2013	0.93	0.94	0.85	0.96	0.98
		[0.88, 0.98]	[0.88, 0.99]	[0.78, 0.90]	[0.89, 1.02]	[0.91, 1.04]
GDP growth						
Consensus	1995–2013	0.99	1.01	1.09		
RBA	1995–2011	1.04	0.97	1.05		
Econometric	1995–2013	0.98	0.98	1.04	1.03	1.03
		[0.93, 1.03]	[0.93, 1.03]	[0.99, 1.09]	[0.99, 1.07]	[0.98, 1.07]
	1980–2013	0.97	0.97	1.04	1.00	1.02
		[0.93, 1.01]	[0.93, 1.01]	[1.00, 1.07]	[0.97, 1.04]	[0.98, 1.05]

Note: Where forecast series have been estimated, a 95 per cent bootstrap confidence interval is reported in brackets

The Consensus and RBA forecasts substantially outperform the autoregressive CPI inflation forecasts, particularly at a short horizon. At longer horizons, a sizeable portion of the improved forecast performance is due to anticipation of the introduction of the GST in 1999/2000. The CPI inflation series used to estimate the econometric forecasts has been adjusted to remove the effects of tax changes. The econometric forecasts are statistically indistinguishable from the autoregressive benchmark over the low-inflation period, but outperform the autoregressive benchmark at longer horizons over the 1980–2013 sample period. This reflects the fact that inflation has become harder to forecast since the adoption of inflation targeting (see Stock and Watson (2007) for US evidence, and Heath, Roberts and Bulman (2004) for Australian evidence). The results are similar for the underlying inflation forecasts: improved forecast performance relative to the autoregressive benchmark is mostly evident only over the 1980–2013 period. For the GDP growth forecasts, there is little evidence of improved performance relative to the autoregressive benchmark. Where comparable, and except for CPI inflation, the autoregressive forecasts perform similarly well to the official RBA forecasts. Overall, the results presented in Table 2 indicate that the econometric forecasts provide a plausible set of expectations for estimation of the SIPC.

Figure 2 shows the time series of RBA and econometric underlying inflation forecasts, at several horizons. The short-horizon econometric forecasts track measured underlying inflation relatively closely. But the long-horizon econometric forecasts did not predict the early 1990s disinflation. The long-horizon forecasts perform substantially worse than the short-horizon forecasts in the early 1990s because they place a relatively low weight on recent inflation outcomes, and a relatively high weight on real-time estimates of the series mean. The relatively high variability of CPI inflation makes the poor performance of long-horizon forecasts during the disinflation less evident (see Figure 3).

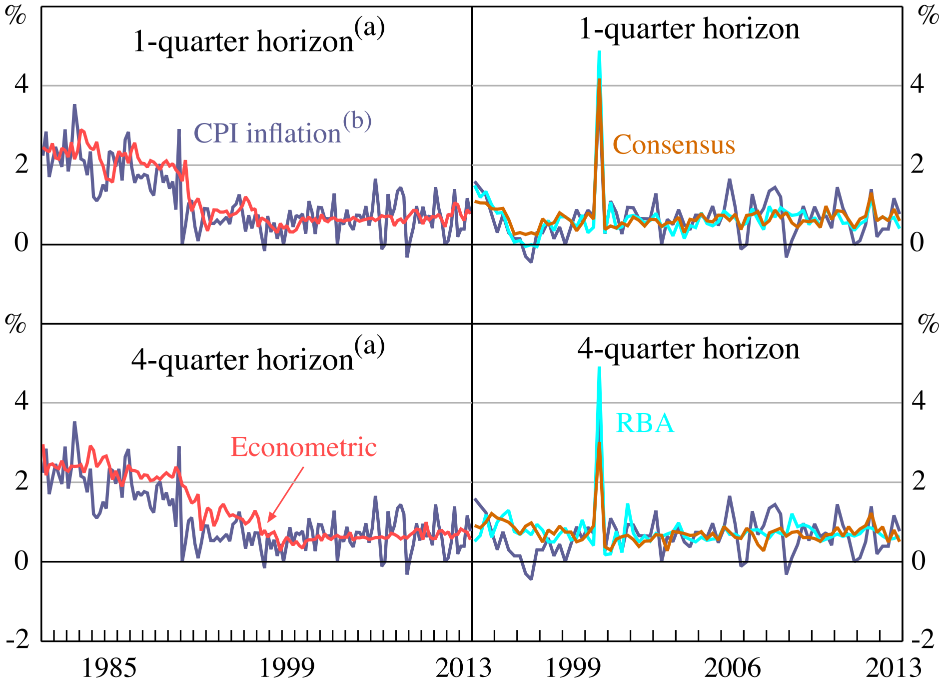
Figure 2: Quarterly Underlying Inflation Forecasts



Note: (a) Actual data

Sources: ABS; Author's calculations; RBA

Figure 3: CPI Quarterly Inflation Forecasts



Notes: (a) Excluding interest charges prior to the September quarter 1998 and adjusted for the tax changes of 1999–2000
(b) Actual data

Sources: ABS; Author's calculations; Consensus Economics; RBA

4. Results

4.1 Low-inflation Period

Table 3 reports estimates for the SIPC over the 1995–2013 period. Using RBA and Consensus forecasts for CPI inflation yields a negative estimate for λ, contradicting the SIPC model, which requires the degree of information rigidity to be between zero and one. There is no evidence of information rigidity, largely because CPI inflation over the low-inflation period has been dominated by idiosyncratic shocks, rather than inertial monetary policy shocks. Some of the evidence against a high degree of information rigidity comes from the tax changes associated with the introduction of the GST. The sharp rise and fall in CPI inflation was accurately incorporated into real-time RBA and Consensus forecasts, which is inconsistent with the inertial dynamics implied by a high degree of information rigidity. Much of the explained variation in CPI inflation for these SIPC equations is accounted for by the 1999/2000 period. For both the RBA and Consensus forecast versions of the SIPC, the estimated degree of real rigidity is very high, indicated by a small estimate for α.

Using the econometric forecasts, which abstract from tax changes, the estimated SIPC indicates a high degree of information rigidity. But the estimated degree of real rigidity is negative, contradicting the assumption that $\alpha > 0$. Furthermore, the amount of the variation in CPI inflation explained by the SIPC is negligible. For SIPC estimates using the econometric forecasts, bootstrap standard errors taking forecast uncertainty into account are reported in brackets and, as with the estimates using RBA and Consensus forecasts, ordinary standard errors are reported in parentheses. See Appendix A for details on the construction of the bootstrap standard errors. In general, the bootstrap standard errors are about an order of magnitude larger than the ordinary standard errors, indicating that the estimated parameters are sensitive to the forecasts.

The estimated SIPC for underlying inflation, using RBA and econometric forecasts, yields an estimated degree of information rigidity implying that firms on average update their information sets about once every seven quarters. Underlying inflation measures remove much of the idiosyncratic variability from CPI inflation, resulting in relatively inertial series that are more consistent with a high degree of information rigidity. However, the estimated degree of real rigidity using the underlying inflation measure remains theoretically inconsistent, and the proportion of variation in underlying inflation explained by the SIPC is modest.

The real rigidity estimates can in part be explained by the small contemporaneous correlation between quarterly inflation and the output gap over the low-inflation period, which implies that the term $\alpha\left[(1-\lambda)/\lambda\right]$ in Equation (2) is small. If the estimated degree of information rigidity is small (λ is close to zero), then the estimated degree of real rigidity must be high (α close to zero). This is the case for the CPI inflation SIPC using RBA and Consensus forecasts. In contrast, if the estimated degree of information rigidity is large, then the term $(1-\lambda)/\lambda$ is small, and the degree of real rigidity is imprecisely estimated, as is the case for the SIPC estimated with underlying inflation.[7]

7 This can be seen by inspection of the standard errors for α: when the estimate for λ is close to unity, the standard errors for α are large.

Table 3: Sticky Information Phillips Curve – 1995–2013

	CPI inflation			Underlying inflation	
	RBA	Consensus	Econometric	RBA	Econometric
Constant: c	0.05	–0.03	0.47	0.40	0.38
	(0.06)	(0.05)	(0.16)	(0.10)	(0.10)
			[–1.49, 1.76]		[–0.51, 1.16]
Real rigidity: α	–0.01	0.02	–0.58	–0.02	–0.30
	(0.03)	(0.04)	(1.07)	(0.16)	(0.24)
			[–5.03, 1.47]		[–1.09, 0.29]
Information rigidity: λ	–0.45	–0.18	0.93	0.87	0.86
	(0.10)	(0.22)	(0.07)	(0.05)	(0.06)
			[–0.36, 1.75]		[–0.84, 2.04]
Import prices: $\gamma \times 10$	–0.16	–0.10	–0.05	0.07	0.08
	(0.09)	(0.12)	(0.11)	(0.04)	(0.05)
			[–0.38, 0.15]		[–0.12, 0.18]
Durbin-Watson	1.63	1.77	1.75	1.30	1.30
R^2	0.63	0.58	0.03	0.12	0.11
Impose $\alpha = 0.1$					
Constant: c	–0.06	–0.06	0.51	0.35	0.39
	(0.07)	(0.10)	(0.18)	(0.11)	(0.13)
			[–1.13, 1.93]		[–0.84, 1.41]
Information rigidity: λ	0.25	0.43	0.94	0.87	0.87
	(0.27)	(0.21)	(0.08)	(0.06)	(0.08)
			[0.28, 1.41]		[–0.13, 1.46]
Import prices: $\gamma \times 10$	–0.01	0.02	–0.03	0.07	0.11
	(0.17)	(0.14)	(0.01)	(0.04)	(0.00)
			[–0.31, 0.15]		[–0.02, 0.19]
Durbin-Watson	1.38	1.28	1.72	1.27	1.23
R^2	0.36	0.42	0.01	0.11	0.07

Notes: Newey-West standard errors are reported in parentheses; where forecast series have been estimated, a 95 per cent bootstrap confidence interval is reported in brackets

To the extent that weak identification affects the estimated output-inflation trade-off, imposing the degree of real rigidity may yield more accurate estimates of the degree of information rigidity. The bottom panel in Table 3 reports SIPC estimates imposing $\alpha = 0.1$, the degree of real rigidity conjectured by Mankiw and Reis (2002). The estimated degree of information rigidity for the underlying inflation SIPC, and the CPI inflation SIPC using econometric forecasts, are largely unaffected by the imposition of $\alpha = 0.1$. This is because the freely-estimated versions of these equations yielded a large estimate for λ, in which case the degree of real rigidity is imprecisely estimated. But for the CPI inflation SIPC estimates using RBA and Consensus forecasts, imposing the value of α has a substantial effect on the estimated degree of information rigidity. The estimated value of λ turns positive, and indicates that firms on average update their information sets about once every 1–2 quarters. But by making inflation more inertial, the rise in λ substantially worsens the fit of the model, indicated by the decline in the R-squared statistic when $\alpha = 0.1$ is imposed.

4.2 Long Sample

The estimates presented thus far exclude the early 1990s disinflation. But an appealing theoretical aspect of the SIPC is its ability to generate costly disinflations, in contrast to the sticky-price model. In fact, Ball (1994) shows that the NKPC predicts a boom in output upon announcement of a credible disinflation. This occurs because firms that are able to adjust their price reset according to the expected new lower level of inflation, raising the real value of money holdings, and stimulating demand (Mankiw 2001). In practice, disinflations are typically contractionary.[8] Including the disinflationary period in the estimation period may improve identification of the SIPC model parameters, and provides a potentially informative sample period to distinguish between the sticky-price and sticky-information models.

8 One reconciliation of the theory and actual experience is to question the credibility of announced disinflations. But Mankiw (2001, p C57–58) argues that this feature of the NKPC cannot be so easily squared with the data: 'Because monetary shocks have a delayed and gradual effect on inflation, in essence we experience a credible announced disinflation every time we get a contractionary shock. Yet we do not get the boom that the model says should accompany it. This means that something is fundamentally wrong with the model'.

Table 4 reports estimates of the SIPC using data for the period 1980–2013, over which only the econometric forecasts are available; estimates are presented for truncation of the SIPC at both a one- and two-year horizon.[9] In each case, the estimated degree of information rigidity is theoretically consistent. For CPI inflation, the estimated values for λ indicate that firms on average update their information set each 3–5 quarters. The estimated degree of information rigidity is larger over the 1980–2013 sample than the 1995–2013 sample largely because CPI inflation behaved inertially during the 1980s and the period of disinflation, which is consistent with the SIPC model. But despite the inertial behaviour of underlying inflation over the 1980–2013 period, the estimated degree of information rigidity is relatively low. This is because the long-horizon underlying inflation forecasts substantially overpredicted inflation during the disinflation (see Figure 2). A high degree of information rigidity would place substantial weight on these poorly performing long-horizon forecasts, reducing the empirical fit of the SIPC.

Because of the weak contemporaneous correlation between inflation and the output gap, the estimated degree of real rigidity is large (α is small) for all SIPC specifications reported in Table 4. Imposing the degree of real rigidity to be $\alpha = 0.1$ has little effect on the estimated degree of information rigidity or the fit of the SIPC, except for the underlying inflation SIPC truncated at a two-year horizon. As explained earlier, when the freely estimated degree of information rigidity is large, the coefficient on the output gap is insensitive to the parameter α. The share of the variation in inflation explained by the SIPC is high, largely because the model captures the mean shift in the early 1990s.

9 See Appendix B for estimates over the shorter 1980–1990 sample period.

Table 4: Sticky Information Phillips Curve – 1980–2013

	CPI inflation		Underlying inflation	
	$J=4$	$J=8$	$J=4$	$J=8$
Constant: c	0.08	0.02	0.00	–0.06
	(0.08)	(0.09)	(0.05)	(0.03)
	[–0.29, 0.33]	[–0.37, 0.24]	[–0.17, 0.10]	[–0.13, –0.02]
Real rigidity: α	0.06	–0.04	0.03	0.00
	(0.09)	(0.24)	(0.04)	(0.01)
	[–3.42, 1.09]	[–1.12, 0.75]	[–1.52, 0.54]	[–0.02, 0.02]
Information rigidity: λ	0.65	0.80	0.50	0.11
	(0.07)	(0.05)	(0.10)	(0.14)
	[–0.52, 1.17]	[–0.07, 1.40]	[–1.18, 1.64]	[–2.02, 0.75]
Import prices: $\gamma \times 10$	0.19	0.16	0.16	0.18
	(0.12)	(0.12)	(0.05)	(0.06)
	[–0.19, 0.49]	[–0.22, 0.45]	[0.04, 0.26]	[–0.02, 0.32]
Durbin-Watson	1.54	1.47	1.11	1.25
R^2	0.59	0.58	0.82	0.82
Davidson-MacKinnon non-nested model tests				
δ_{SI}	0.25	0.14	0.54	1.52
	(0.37)	(0.27)	(0.56)	(1.01)
	[–0.85, 0.89]	[–0.54, 0.48]	[–0.88, 1.43]	[–8.16, 7.46]
δ_{SP}	0.56	0.79	–0.10	–0.10
	(0.58)	(0.13)	(0.06)	(0.06)
	[–6.67, 5.55]	[–1.36, 2.48]	[–0.30, –0.05]	[–0.29, –0.03]
Impose $\alpha = 0.1$				
Constant: c	0.10	0.03	0.05	–0.08
	(0.08)	(0.09)	(0.06)	(0.04)
	[–0.19, 0.33]	[–0.31, 0.26]	[–0.25, 0.19]	[–0.18, –0.05]
Information rigidity: λ	0.66	0.80	0.58	0.51
	(0.07)	(0.05)	(0.09)	(0.17)
	[0.15, 1.04]	[0.44, 1.05]	[–0.02, 0.98]	[–0.06, 1.00]
Import prices: $\gamma \times 10$	0.19	0.17	0.15	0.19
	(0.12)	(0.12)	(0.05)	(0.08)
	[–0.06, 0.40]	[–0.01, 0.03]	[0.09, 0.19]	[0.04, 0.26]
Durbin-Watson	1.52	1.44	1.03	0.92
R^2	0.59	0.57	0.81	0.78

Notes: Newey-West standard errors are reported in parentheses; bootstrap 95 per cent confidence intervals that account for uncertainty associated with estimation of the forecasts are reported in brackets

4.3 Comparing the SIPC and the NKPC

For the 1980–2013 period as a whole, the SIPC appears to provide a plausible model of inflation. But is the sticky-information model a better description of inflation dynamics than the sticky-price model? Because the SIPC and NKPC models are non-nested, discriminating between the two models is not as straightforward as imposing restrictions on the estimated parameters of the SIPC. The first set of tests used to discriminate between the two price-setting models are Davidson and MacKinnon (2002) non-nested model tests. Under the null hypothesis that the sticky-information model is correct, the SIPC is augmented with NKPC fitted values and re-estimated:

$$\begin{aligned}\pi_t = \; & c \; + \left[\tfrac{1-\lambda}{\lambda}\right] \alpha x_t + (1-\lambda) \textstyle\sum_{j=0}^{J} \lambda^j E_{t-j-1} \left[\pi_t + \alpha \Delta x_t\right] + \gamma \hat{\pi}_t^m \\ & + \delta_{SP} \hat{\pi}_t^{NKPC} + \varepsilon_t,\end{aligned} \tag{9}$$

where $\hat{\pi}_t^{NKPC}$ is the fitted values from estimation of the NKPC, Equation (7). Under the null hypothesis that the SIPC is correct, the NKPC fitted values have no additional explanatory power for inflation, and the coefficient δ_{SP} is insignificantly different from zero. Rejection of the hypothesis $\delta_{SP} = 0$ provides evidence in favour of the NKPC. Similarly, under the null hypothesis that the sticky-price model is correct, the NKPC model is augmented with SIPC fitted values and re-estimated:

$$\pi_t = c + \rho x_t + \beta E_t \left[\pi_{t+1}\right] + \gamma \hat{\pi}_t^m + \delta_{SI} \hat{\pi}_t^{SIPC} + \varepsilon_t, \tag{10}$$

where $\hat{\pi}_t^{SIPC}$ is the fitted values from estimation of the SIPC, Equation (4). Rejection of the hypothesis $\delta_{SI} = 0$ provides evidence in favour of the SIPC model.

The middle panel of Table 4 reports estimates for these non-nested model tests. For each inflation measure and truncation length, we cannot reject the null hypothesis $\delta_{SP} = 0$ in testing the null hypothesis that the SIPC is the correct model, or the hypothesis that $\delta_{SI} = 0$ in testing the null hypothesis that the NKPC is the correct model. This is true even with ordinary standard errors, that do not allow for the fact that the forecasts are generated regressors. Thus, the Davidson and MacKinnon (2002) non-nested model tests provide inconclusive evidence.

Estimation of an encompassing model provides an alternative means to test the SIPC against the NKPC. This involves jointly estimating the parameters for each model:

$$\pi_t = c + \omega \pi_t^{SIPC}(\alpha, \lambda) + (1-\omega)\pi_t^{NKPC}(\rho, \beta) + \gamma \hat{\pi}_t^m + \varepsilon_t, \tag{11}$$

where ω is the weight on the SIPC model, $\pi_t^{SIPC}(\alpha, \lambda)$ is SIPC inflation, given by the right-hand-side of Equation (4) excluding the import price term, and $\pi_t^{NKPC}(\rho, \beta)$ is NKPC inflation, given by the right-hand-side of Equation (7), excluding the import price term. Because the encompassing regression is highly non-linear in five parameters, the SIPC parameters are restricted to be theoretically consistent, $\alpha > 0$ and $0 < \lambda < 1$, and the sum of the weights on the models is constrained to unity, $0 < \omega < 1$.

The first two columns of Table 5 report encompassing test results, for CPI and underlying inflation. The results suggest that the forward-looking NKPC is a better description of inflation dynamics over the 1980–2013 period than the SIPC model: the coefficient ω, the weight on the SIPC model relative to the NKPC model, is small. Because the estimated weight on the SIPC is small, the SIPC parameters α and λ are imprecisely estimated: as ω approaches zero, a wide range of coefficients for the SIPC fits the data almost equally well. Because the output gap enters both the SIPC and the NKPC when ω is above zero, the encompassing test cannot precisely pin down the output gap parameters α and ρ in each model: identification comes only via the non-linearity in the SIPC. This imprecision is evident for the underlying inflation encompassing model.

The NKPC model appears to fit the data better in part because, as shown in Figure 2, the long-horizon real-time forecasts substantially overpredicted inflation relative to the short-horizon forecasts during the early 1990s disinflation. The real-time forecast error was smaller for short-horizon forecasts because they place more weight on recent inflation outcomes and less weight on the estimated long-run mean inflation rate, which was slow to update during the disinflationary period. Thus, the SIPC model, which places weight on dated long-horizon forecasts, substantially overpredicts inflation during the disinflation, except with very low levels of information rigidity. This is particularly apparent with the calibration of the SIPC proposed by Mankiw and Reis (2002), as shown in Figure 4.

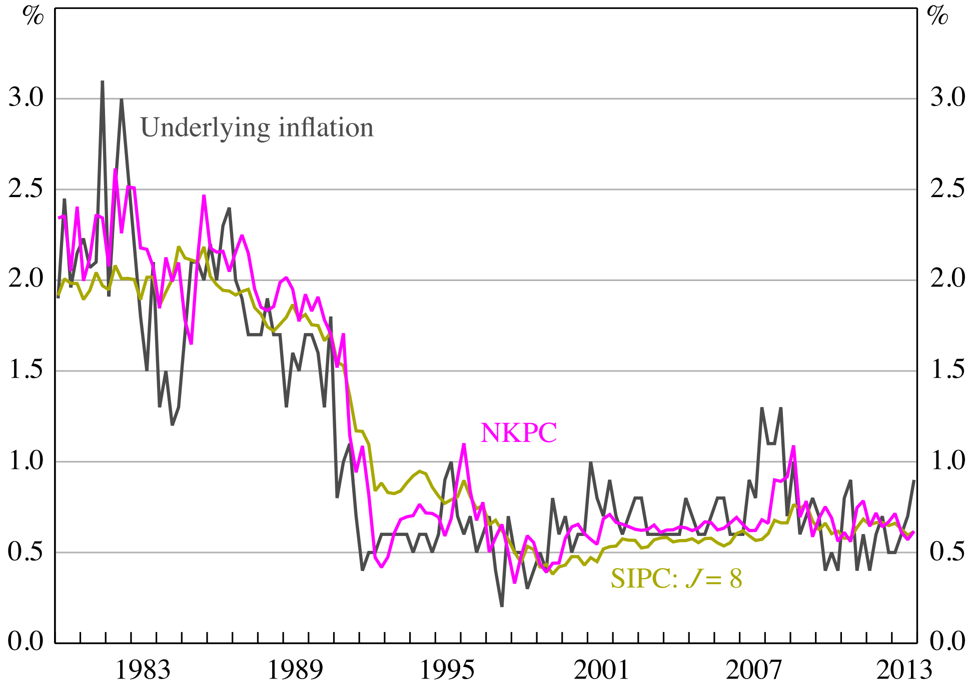
Table 5: Encompassing Model Test – 1980–2013

	Encompassing test		NKPC		Hybrid NKPC	
	CPI inflation $J=8$	Underlying inflation $J=8$	CPI inflation	Underlying inflation	CPI inflation	Underlying inflation
Constant	0.08	0.05	0.09	0.07	0.09	0.06
	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)
	[–0.15, 0.23]	[–0.04, 0.13]	[–0.15, 0.24]	[–0.08, 0.20]	[–0.12, 0.23]	[–0.07, 0.15]
α	2.68	0.75				
	(204.6)	(2.98)				
	$[-\infty, \infty]$	[–25.28, 23.03]				
λ	0.95	0.18				
	(22.64)	(1.14)				
	[–142.64, 112.51]	[–1.26, 1.53]				
ρ	0.02	–0.62	0.02	0.00	0.02	0.00
	(1.01)	(2.72)	(0.03)	(0.02)	(0.03)	(0.02)
	[–2.04, 1.66]	[–2.14, 0.35]	[–0.11, 0.11]	[–0.07, 0.06]	[–0.10, 0.11]	[–0.08, 0.06]
β	0.85	0.89	0.84	0.90	0.80	0.82
	(2.71)	(0.05)	(0.06)	(0.05)	(0.16)	(0.20)
	[–6.01, 6.39]	[0.76, 0.98]	[0.61, 1.03]	[0.68, 1.03]	[0.11, 1.32]	[–0.61, 1.62]
$\gamma \times 10$	0.12	0.11	0.12	0.10	0.12	0.09
	(0.11)	(0.04)	(0.11)	(0.04)	(0.12)	(0.04)
	[–0.15, 0.36]	[0.01, 0.18]	[–0.14, 0.33]	[0.02, 0.16]	[–0.25, 0.35]	[0.03, 0.16]
ω	0.01	0.15				
	(3.09)	(0.42)				
	[–0.16, 0.11]	[–0.17, 0.41]				
LDV					0.05	0.08
					(0.16)	(0.18)
					[–0.72, 0.51]	[–0.39, 0.47]
DW	1.91	1.91	1.91	2.06	1.98	2.17
R^2	0.60	0.84	0.60	0.84	0.60	0.84

Notes: Newey-West standard errors are reported in parentheses; bootstrap 95 per cent confidence intervals that account for uncertainty associated with estimation of the forecasts are reported in brackets; LDV denotes lagged dependent variable; DW denotes Durbin-Watson

Separately estimated NKPC equations reinforce the evidence in favour of the sticky-price model. The estimated coefficient on forward-looking NKPC inflation is similar in the encompassing model and the NKPC model, and the fit of the NKPC model for CPI and underlying inflation is no worse than the encompassing model (see Table 5). The hybrid NKPC model augments the NKPC with a lagged dependent variable, providing a reduced-form means of capturing the inflation inertia that the SIPC builds in from microfoundations. The estimated weight on lagged inflation is small, consistent with the small estimated weight on the SIPC in the encompassing model.

Figure 4: Predicted Quarterly Underlying Inflation



Note: SIPC and NKPC have been calibrated using Mankiw and Reis (2002) parameter values: $\alpha = 0.1$ and $\lambda = 0.75$

4.4 Adaptive Expectations Phillips Curve

The previous section sought to distinguish between the non-nested SIPC and NKPC models, the two most prominent Phillips curve models in the literature. A nested alternative to the SIPC is the adaptive expectations Phillips curve (AEPC). The SIPC model reduces to a distributed-lag AEPC under the assumption that expected inflation is equal to current inflation, and expected changes in the output gap are equal to zero. Accordingly, the SIPC can be expressed as an AEPC plus expectational deviations between the two models:

$$\begin{aligned}\pi_t = \; c \; &+ \left[\tfrac{1-\lambda}{\lambda}\right] \alpha x_t + (1-\lambda) \textstyle\sum_{j=0}^{J} \lambda^j \pi_{t-j} \\ &+ \phi\,(1-\lambda) \textstyle\sum_{j=0}^{J} \lambda^j E_{t-j-1}\left[\left(\pi_t - \pi_{t-j}\right) + \alpha \Delta x_t\right] + \gamma \hat{\pi}_t^m + \varepsilon_t.\end{aligned} \tag{12}$$

Table 6 reports parameter estimates for Equation (12). Under the null hypothesis that the SIPC is correct $\phi = 1$, and under the null hypothesis that the AEPC is correct $\phi = 0$. Empirically distinguishing between the two models requires the SIPC rational expectations forecasts to substantially outperform the AEPC random walk forecasts; if the rational expectations forecasts are identical to the random walk forecasts, the SIPC model is indistinguishable from a distributed-lag AEPC. Particularly over the low-inflation period, the random walk benchmark has been shown to be difficult to improve upon: Atkeson and Ohanian (2001) find that Phillips curve-based forecasts do not outperform random walk forecasts for US inflation after 1984, and Heath *et al* (2004) report similar evidence for Australia. This means that tests seeking to distinguish between the SIPC and AEPC models have low power. Reflecting this, the bootstrap confidence intervals for the parameter ϕ in Equation (12) are wide enough to be consistent with both the SIPC and AEPC models.

Although the SIPC and AEPC equations have similar fit, they have different theoretical implications for the behaviour of inflation. Mankiw and Reis (2002) show that, in response to a demand shock, inflation and output overshoot in the AEPC model, but behave inertially and do not overshoot in the SIPC model. Tests based on the dynamic response to shocks may be more informative for distinguishing between the SIPC and AEPC models than fit comparisons. This is left for further work.

Table 6: Nested Adaptive Expectations Phillips Curve – 1980–2013

	CPI inflation		Underlying inflation	
	$J=4$	$J=8$	$J=4$	$J=8$
Constant	0.07	0.03	0.02	–0.02
	(0.07)	(0.06)	(0.05)	(0.02)
	[–0.11, 0.19]	[–0.24, 0.12]	[–0.14, 0.10]	[–0.07, –0.00]
α	0.08	0.13	0.01	0.04
	(0.05)	(0.12)	(0.03)	(0.02)
	[–0.20, 0.30]	[–1.64, 1.08]	[–0.13, 0.09]	[–0.83, 0.34]
λ	0.60	0.74	0.52	0.44
	(0.07)	(0.06)	(0.10)	(0.10)
	[0.26, 0.73]	[–1.23, 0.89]	[–2.02, 2.39]	[–2.75, 2.45]
$\gamma \times 10$	0.13	0.15	0.15	0.12
	(0.12)	(0.12)	(0.05)	(0.04)
	[–0.30, 0.46]	[–0.31, 0.47]	[0.03, 0.30]	[–0.04, 0.25]
ϕ	0.54	0.32	1.80	0.22
	(0.18)	(0.20)	(0.34)	(0.13)
	[–0.28, 1.24]	[–0.93, 0.97]	[–9.90, 13.00]	[–0.18, 0.58]
Durbin-Watson	1.88	1.84	1.20	2.10
R^2	0.61	0.61	0.83	0.86

Notes: Newey-West standard errors are reported in parentheses; bootstrap 95 per cent confidence intervals that account for uncertainty associated with estimation of the forecasts are reported in brackets

5. Conclusion

The Sticky Information Phillips Curve provides a theoretically appealing alternative to the New-Keynesian Phillips curve. The key assumption that macroeconomic news disseminates slowly throughout the population is intuitively appealing, and enables the model to match empirical estimates of the dynamic response of inflation to monetary policy shocks, unlike the NKPC. This paper provides the first estimates of the SIPC for Australia. Overall, the results do not lend strong support to the model. The estimated parameters are sensitive to sample periods and inflation measures, and are theoretically inconsistent for several specifications.

The disappointing empirical performance of the SIPC can be in part explained by a change in the behaviour of inflation since the introduction of inflation targeting: the inertial trend component of inflation – that the SIPC provides a microfoundation for – accounts for a smaller share of the overall variability in inflation than in the past. Accordingly, including data prior to the inflation-targeting period in the estimation sample improves the performance of the SIPC. However, the NKPC appears to fit the data at least as well as the SIPC. The performance of the SIPC is particularly affected by the weak connection between the real and nominal side of the model. Furthermore, the NKPC is better able to explain the disinflation because it places less weight on long-horizon inflation forecasts, which (based on model estimates) substantially overpredicted inflation in the early 1990s. Taking account of differences in forecast measures used and restrictions placed on the model parameters, these findings are broadly in line with evidence for the United States and Europe.

While the results provide little support for the SIPC, particularly over the low-inflation period, they should not necessarily be taken as evidence against the importance of information rigidities. Since the introduction of inflation targeting, it has become more difficult to model inflation. The share of variation in inflation explained by a wide range of models has fallen together with the overall variation in inflation. Few models can now outperform a forecast of constant inflation of 2.5 per cent (midpoint of the RBA's target band). The poor performance of the SIPC over the low-inflation period in part reflects this more general finding, and not necessarily a rejection of the importance of information rigidities. Alternate tests find evidence consistent with information rigidities. For example, Coibion and Gorodnichenko (2012) show that the response of survey forecast errors to economic shocks supports the sticky-information model. The behaviour of consumer inflation expectations is also consistent with slow diffusion of economic news throughout the population (Carroll 2003). The core assumption of the SIPC that macroeconomic news disseminates slowly throughout the population is attractive, and the SIPC provides a useful framework for thinking through the effects on inflation. One possible means of improving the performance of the SIPC might be to introduce state-dependence in the frequency with which firms update their expectations. This would allow inflation to respond quickly to some shocks, but retain the predicted inertial response to monetary policy shocks.

Appendix A: Confidence Intervals for Econometric Forecasts

Ordinary standard errors generated by estimation of the SIPC with the econometric forecasts do not take forecast uncertainty into account. This is the generated regressors problem discussed by Pagan (1986). To allow for uncertainty caused by estimation of the forecasts, the bootstrap procedure outlined by Kahn and Zhu (2006) is followed. The first step in the procedure requires generating alternate histories of the data. The vector autoregression model

$$Y_t = \beta(L)Y_t + \varepsilon_t \tag{A1}$$

is estimated using each of the forecast and explanatory variables listed in Table 1, for the period 1964–2013. The lag length is set at 8 quarters, guided by the AIC criteria. The first alternate history of data is created by repeated resampling (with replacement) from the vector of estimated residuals $\hat{\varepsilon}_t$, using the first L-quarters of data for the lagged dependent variables. Data for an initial burn-in-period of 100 quarters is discarded, leaving a simulated set of data for the period 1964–2013. This procedure is repeated $N = 500$ times to produce a set of alternate histories of data.

For each history of data, the forecast procedure outlined in Section 3.1 is used to estimate econometric forecasts for CPI inflation, underlying inflation and the change in the output gap. Use of each alternate set of forecasts to estimate the SIPC produces a distribution of parameter estimates and standard errors for each regression coefficient. For each set of data i and regression parameter β_k the test statistic

$$t^*_{i,k} = \frac{\hat{\beta}_{k,i} - \hat{\beta}_k}{\hat{\sigma}_{k,i}} \tag{A2}$$

is calculated, where $\hat{\beta}_{k,i}$ is the estimated regression coefficient for parameter k using alternate history of data i, $\hat{\sigma}_{k,i}$ is its estimated standard error, and $\hat{\beta}_k$ is the parameter estimate using the observed data. Taking the 2.5 and 97.5 percentiles of $t^*_{i,k}$ produces bootstrapped 95 per cent critical values $t^*_{L,k}$ and $t^*_{U,k}$ for regression parameter k. Using these critical values, a percentile-t interval can be calculated for regression parameter k:

$$\left[\hat{\beta}_k - t^*_{U,k}\hat{\sigma}_k, \hat{\beta}_k - t^*_{L,k}\hat{\sigma}_k\right]. \tag{A3}$$

Note that the percentile-t confidence interval is not guaranteed to contain the parameter estimate $\hat{\beta}_k$. For example, suppose each bootstrapped estimate $\hat{\beta}_{k,i} > \hat{\beta}_k$, then $t^*_{L,k} > 0$ and the upper bound of the confidence interval is less than the parameter estimate $\hat{\beta}_k$.

Appendix B: SIPC Estimates for 1980–1990

Table B1: Sticky Information Phillips Curve – 1980–1990

	CPI inflation		Underlying inflation	
	$J = 4$	$J = 8$	$J = 4$	$J = 8$
Constant: c	1.55	0.94	–0.10	–0.09
	(0.43)	(0.50)	(0.06)	(0.05)
	[–11.70, 12.68]	[–8.54, 9.41]	[–0.32, 0.07]	[–0.41, 0.09]
Real rigidity: α	–1.21	–1.14	0.00	0.00
	(1.01)	(0.84)	(0.01)	(0.01)
	[–5.60, 1.56]	[–4.79, 1.17]	[–0.03, 0.02]	[–0.05, 0.03]
Information rigidity: λ	0.92	0.91	0.11	0.12
	(0.06)	(0.05)	(0.19)	(0.19)
	[–0.06, 1.70]	[–0.58, 1.61]	[–2.68, 1.62]	[–3.50, 1.45]
Import prices: $\gamma \times 10$	0.55	0.48	0.25	0.25
	(0.08)	(0.11)	(0.09)	(0.09)
	[–0.42, 1.19]	[–0.08, 0.13]	[–1.03, 0.74]	[–1.01, 0.72]
Durbin-Watson	1.56	1.54	1.48	1.50
R^2	0.32	0.31	0.37	0.38

Notes: Newey-West standard errors are reported in parentheses; bootstrap 95 per cent confidence intervals that account for uncertainty associated with estimation of the forecasts are reported in brackets

References

Atkeson A and LE Ohanian (2001), 'Are Phillips Curves Useful for Forecasting Inflation?', Federal Reserve Bank of Minneapolis *Quarterly Review*, 25(1), pp 2–11.

Ball L (1994), 'Credible Disinflation with Staggered Price-Setting', *The American Economic Review*, 84(1), pp 282–289.

Blanchard OJ and N Kiyotaki (1987), 'Monopolistic Competition and the Effects of Aggregate Demand', *The American Economic Review*, 77(4), pp 647–666.

Carroll CD (2003), 'Macroeconomic Expectations of Households and Professional Forecasters', *The Quarterly Journal of Economics*, 118(1), pp 269–298.

Christiano LJ, M Eichenbaum and CL Evans (1999), 'Monetary Policy Shocks: What Have We Learned and to What End?', in JB Taylor and M Woodford (eds), *Handbook of Macroeconomics: Volume 1A*, Handbooks in Economics, 15, Elsevier Science B.V., Amsterdam, pp 65–148.

Coibion O (2010), 'Testing the Sticky Information Phillips Curve', *Review of Economics and Statistics*, 92(1), pp 87–101.

Coibion O and Y Gorodnichenko (2012), 'What Can Survey Forecasts Tell Us about Information Rigidities?', *Journal of Political Economy*, 120(1), pp 116–159.

Davidson R and JG MacKinnon (2002), 'Bootstrap *J* Tests of Nonnested Linear Regression Models', *Journal of Econometrics*, 109(1), pp 167–193.

Döpke J, J Dovern, U Fritsche and J Slacalek (2008), 'Sticky Information Phillips Curves: European Evidence', *Journal of Money, Credit and Banking*, 40(7), pp 1513–1519.

Fuhrer J and G Moore (1995), 'Inflation Persistence', *The Quarterly Journal of Economics*, 110(1), pp 127–159.

Galí J and M Gertler (1999), 'Inflation Dynamics: A Structural Econometric Analysis', *Journal of Monetary Economics*, 44(2), pp 195–222.

Galí J, M Gertler and JD López-Salido (2005), 'Robustness of the Estimates of the Hybrid New Keynesian Phillips Curve', *Journal of Monetary Economics*, 52(6), pp 1107–1118.

Heath A, I Roberts and T Bulman (2004), 'Inflation in Australia: Measurement and Modelling', in C Kent and S Guttmann (eds), *The Future of Inflation Targeting*, Proceedings of a Conference, Reserve Bank of Australia, Sydney, pp 167–207.

Khan H and Z Zhu (2006), 'Estimates of the Sticky-Information Phillips Curve for the United States', *Journal of Money, Credit and Banking*, 38(1), pp 195–207.

Kiley MT (2007), 'A Quantitative Comparison of Sticky-Price and Sticky-Information Models of Price-Setting', *Journal of Money, Credit and Banking*, 39(Supplement 1), pp 101–125.

Korenok O (2008), 'Empirical Comparison of Sticky Price and Sticky Information Models', *Journal of Macroeconomics*, 30(3), pp 906–927.

Lucas Jr RE (1973), 'Some International Evidence on Output-Inflation Tradeoffs', *The American Economic Review*, 63(3), pp 326–334.

Mankiw NG (2001), 'The Inexorable and Mysterious Tradeoff Between Inflation and Unemployment', *The Economic Journal*, 111(471), pp C45–C61.

Mankiw NG and R Reis (2002), 'Sticky Information Versus Sticky Prices: A Proposal To Replace the New Keynesian Phillips Curve', *The Quarterly Journal of Economics*, 117(4), pp 1295–1328.

Mavroeidis S, M Plagborg-Møller and JH Stock (2014), 'Empirical Evidence on Inflation Expectations in the New Keynesian Phillips Curve', *Journal of Economic Literature*, 52(1), pp 124–188.

Norman D and A Richards (2010), 'Modelling Inflation in Australia', RBA Research Discussion Paper No 2010-03.

Pagan A (1986), 'Two Stage and Related Estimators and Their Applications', *The Review of Economic Studies*, 53(4), pp 517–538.

Reis R (2006), 'Inattentive Producers', *The Review of Economic Studies*, 73(3), pp 793–821.

Smets F and R Wouters (2007), 'Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach', *The American Economic Review*, 97(3), pp 586–606.

Stock JH and MW Watson (1999), 'Forecasting Inflation', *Journal of Monetary Economics*, 44(2), pp 293–335.

Stock JH and MW Watson (2003), 'Forecasting Output and Inflation: The Role of Asset Prices', *Journal of Economic Literature*, 41(3), pp 788–829.

Stock JH and MW Watson (2004), 'Combination Forecasts of Output Growth in a Seven-Country Data Set', *Journal of Forecasting*, 23(6), pp 405–430.

Stock JH and MW Watson (2007), 'Why has U.S. Inflation Become Harder to Forecast?', *Journal of Money, Credit and Banking*, 39(Supplement s1), pp 3–33.

Tulip P and S Wallace (2012), 'Estimates of Uncertainty around the RBA's Forecasts', RBA Research Discussion Paper No 2012-07.

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