TESTING THE STICKY INFORMATION PHILLIPS CURVE

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Abstract—I consider the empirical evidence for the sticky information model relative to the basic sticky price model, conditional on historical measures of inflation forecasts. The estimated structural parameters are inconsistent with an underlying sticky information model and the sticky information Phillips curve is statistically dominated by the new Keynesian Phillips curve. I find that the poor performance of the sticky information approach is driven by two key elements. First, the sticky information model underestimates inflation in the 1970s and overestimates inflation since the 1980s. Second, predicted inflation from the sticky information model is excessively smooth.

I. Introduction

EMPIRICAL research on the response of the economy to monetary policy shocks has identified important stylized facts that can be used to differentiate among competing models.[1] The delayed response of inflation to such shocks has been of primary interest, because the basic sticky price model cannot replicate this key feature of the data.[2] As a result, much recent research has been devoted to developing models that can match this stylized fact. While some of this work has been done within the context of sticky price models, others have proposed dropping the assumption of sticky prices entirely and focusing instead on informational rigidities.[3] A leading example is the sticky information model of Mankiw and Reis (2002), in which firms update their information infrequently according to a time-dependent process but are free to change prices at all times.

The gradual diffusion of information across the population, the key assumption in the sticky information model, has received some empirical support. For example, Carroll (2003) estimates the rate of diffusion of information from professional forecasters to the general population from an epidemiological model and finds results in line with those assumed by Mankiw and Reis. Dopke et al. (2008) provide similar support for the diffusion of information from forecasters to households in European countries. Mankiw and Reis (2003) estimate a sticky information model applied to wage setting and find that the average wage setter updates his or her information about once per year. Khan and Zhu (2006) directly estimate the structural parameters of the sticky information model applied to price setting and conclude that the evidence is not inconsistent with firms updating their information approximately once a year. Klenow and Willis (2007) find microlevel evidence consistent with firms responding to old information in price-setting decisions.

The empirical approach used in this paper follows the distinction drawn by Carroll (2003) between the formation of expectations by professional forecasters and the diffusion of those forecasts to the population. Sticky information is interpreted as a gradual (time-dependent) diffusion of forecasts from professional forecasters to firms, combined with the additional assumption that price changes are costless. The sticky information Phillips curve (SIPC) then gives the relationship between inflation and the output gap conditional on past forecasts of the current state. One can similarly derive the new Keynesian Phillips curve (NKPC) conditional on professional forecasts by assuming a time-dependent process for changing prices with the additional assumption of costless acquisition of professional forecasts. The purpose of writing these models conditional on inflation forecasts is to separate two issues: whether forecasts are consistent with rational expectations and whether price-setting decisions should best be modeled as sticky prices or sticky information. Previous work on assessing the validity of these models has imposed rational expectations on the forecasts, making the empirical exercise a joint test of price-setting decisions and rational expectations. The approach taken here allows us to separate the two and focus on the question of the validity of each price-setting assumption conditional on observed historical forecasts.

This distinction proves to have important implications for the empirical results. Whereas previous work has found little evidence strongly favoring sticky prices or sticky information, the results of this paper are strongly at odds with the sticky information assumptions. When historical survey measures of inflation forecasts are used, the estimated structural parameters of the SIPC point to no statistically significant degree of information rigidity; moreover, there is no discernible link between the nominal side and the real side of the economy. The SIPC, since the 1970s, can thus be rejected on structural grounds. Second, the SIPC is also strongly rejected statistically in favor of the NKPC, the very model that it was supposed to replace.

I show that this rejection of the SIPC is due to two elements. The first is a real-time forecast error effect.

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[1] See Christiano, Eichenbaum, and Evans (1999).

[2] Mankiw (2001) emphasizes this point. Other failures of the basic sticky price model include predicting costless deflations, economic booms under preannounced credible disinflations (Ball, 1994), and failing to reproduce the positive correlations between changes in inflation and the level of output.

[3] In the context of sticky price models, Gali and Gertler (1999) add rule-of-thumb firms to a sticky price model and derive a hybrid NKPC. Trabandt (2005) shows that such a model can yield a delayed response of inflation to monetary policy shocks. Christiano, Eichenbaum, and Evans (2005) allow sticky price firms to index their prices to some measure of inflation in non-reoptimizing periods. Calvo, Celasun, and Kumhof (2003) allow sticky price firms to choose a reset price and a rate at which prices will be automatically increased.

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Professional forecasters consistently underestimated inflation in the 1970s but overestimated inflation in the 1980s and 1990s. This feature of forecasts is increasingly true at longer forecast horizons. Because the SIPC places significant weight on older forecasts of current inflation, this leads to predicted inflation being too low in the 1970s and too high since the 1980s. The real-time forecast error effect plays an important role in explaining why the estimated degree of information rigidity is close to zero. Importantly, this effect is absent when one uses in-sample forecasts, as implicitly done in Dupor, Kitamura, and Tsuruga (forthcoming), Kiley (2007), Korenok (2008), and Korenok, Radchenko, and Swanson (2007). Thus, whereas previous work has demonstrated that relying on historical inflation forecasts helps the NKPC empirically (see Roberts, 1995, 1997), I show that it impairs the ability of the SIPC to match the data.

A second contribution of the paper is to identify another implication of the SIPC at odds with the data, which I refer to as the inflation inertia effect: predicted inflation from the SIPC using the preferred parameter estimates of Mankiw and Reis is excessively persistent and insufficiently volatile. This result, unlike the real-time forecast error effect, is robust to the forecasts used. The basic sticky price model comes much closer to matching both the persistence and volatility of inflation conditional on inflation forecasts and the output gap. This result is particularly surprising given that the sticky information model was designed explicitly to account for inflation inertia missing from the sticky price model.

The paper also attempts to explain the fact that estimates of the degree of information rigidity from the SIPC are very sensitive to the time period. While the estimates over the whole sample point to no information rigidity at all, the subsample estimates using data since 1984 are consistent with firms acquiring new forecasts less than once a year on average, although the SIPC continues to be dominated by the NKPC statistically even in the subsample analysis. I argue that the high estimated levels of information rigidity are likely to be capturing the fact that forecast errors were highly predictable over this time period. Because the structural form of the SIPC is very similar to tests of the rationality of the forecasts, periods of predictable forecast errors can mistakenly lead one to conclude that there is a high level of sticky information in price-setting decisions when in fact there is none. I illustrate this using the sticky price and imperfect information model of Erceg and Levin (2003), which delivers a pattern of predictable forecast errors in subsamples similar to that observed in the data, even though there is no delay in the diffusion of information from professional forecasters to firms (i.e., no sticky information in the model). I estimate the SIPC in Monte Carlo simulations of this model and closely replicate the empirical findings from the U.S. data over the whole time sample, as well as since the mid-1980s.

These results thus cast doubt on the empirical support for sticky information in price-setting decisions and are more consistent with a sticky price model. However, an important caveat is that the estimation is conditional on historical forecasts. These measures exhibit predictable forecast errors over short horizons as well as disagreement among forecasters, features that are consistent with informational rigidities at the level of professional forecasters. Thus, one should be wary of concluding that information rigidities are unimportant. Instead, one possible interpretation of these results is that modeling firms as sticky price agents that keep close track of professional forecasts could be an adequate representation, but more care needs to be devoted to understanding the rigidities affecting the formation of expectations by professional forecasters. The nature of these informational rigidities remains an open question: perhaps sticky information as suggested by Mankiw, Reis, and Wolfers (2003), imperfect information as in Erceg and Levin (2003), or some alternative mechanism.

The structure of the paper is as follows. Section II presents the econometric approach used to estimate the SIPC as well as the nonnested model tests. Section III presents and discusses the baseline results. Section IV considers some robustness checks, while section V contains a discussion and interpretation of the results. Section VI concludes.

II. Empirical Approach

The goal of the paper is to evaluate the empirical support for the SIPC relative to the basic sticky price model. I do this conditional on historical forecasts. Specifically, I first follow Carroll (2003) and assume that each quarter, professional forecasters generate a set of forecasts of macroeconomic variables denoted by $F_t[(\cdot)]$. There is a continuum of firms, each of which knows that its instantaneously optimal price is given by

$$p_t^{\#}(j) = p_t + \alpha x_t,$$

where p_t is the aggregate price level, x_t is the output gap, and α is the degree of real rigidity.

In general, one could assume that both the acquisition of new forecasts and changing prices are costly. Instead, I will focus on the two extreme cases: the basic sticky information and sticky price models. Following Mankiw and Reis (MR henceforth), the sticky information model consists of two assumptions. First, the acquisition of new forecasts by firms follows a Poisson process in which there is a probability $1 - \lambda$ that any given firm will acquire a new set of forecasts. Second, price changes are costless. Jointly, these two assumptions yield the SIPC,

$$\pi_t = \frac{(1-\lambda)}{\lambda}\alpha x_t + (1-\lambda)\sum_{j=0}^{\infty}\lambda^j F_{t-1-j}(\pi_t + \alpha\Delta x_t),$$

which relates inflation to the output gap and past forecasts of current inflation and changes in the output gap.[4]

Alternatively, one can reverse the assumptions: the acquisition of forecasts is costless and immediate, whereas price changes are costly. Assuming a Poisson process for changing prices, in which $(1 - \gamma)$ is the probability of changing prices each quarter, we get the NKPC,

$$\pi_t = \frac{(1 - \beta\gamma)(1 - \gamma)}{\gamma} \alpha x_t + \beta F_t \pi_{t+1},$$

which relates inflation to the current output gap and the current forecast of future inflation.[5] The key difference lies in the timing of the expectations in each Phillips curve: the sticky price model implies that the relationship between the nominal and the real side of the economy is conditional on current expectations of future inflation, whereas the sticky information model implies that past forecasts of the current state are the relevant measure of expectations in the Phillips curve. This distinction reflects the alternative assumptions about the diffusion of information and the costliness of price changes underlying each model.

To assess the empirical support for the SIPC, I use two sets of criteria. The first is whether estimation of the structural parameters of the SIPC yields values consistent with the theory of the model. The second is to compare its performance statistically to the NKPC. I consider first how to adequately estimate the structural parameters of the SIPC and then turn to the issue of assessing its validity relative to the sticky price model.

A. *Estimating the Sticky Information Phillips Curve*

To assess the empirical validity of the SIPC, I first augment the SIPC with an error term ε_t, assumed to be independent and identically distributed (i.i.d.):[6]

$$\pi_t = \frac{(1 - \lambda)}{\lambda} \alpha x_t + (1 - \lambda) \times \sum_{j=0}^{\infty} \lambda^j F_{t-1-j}(\pi_t + \alpha \Delta x_t) + \varepsilon_t. \tag{1}$$

Estimating λ and α using equation (1) presents several difficulties. First, the output gap on the right-hand side will tend to be correlated with the error term.[7] This endogeneity issue can typically be addressed by instrumental variables. However, the infinite amount of regressors on the right-hand side must be truncated, adding a source of error that will not be uncorrelated with lagged instruments. Therefore, the identification condition that instruments be uncorrelated with the error term will typically fail. Second, other than the output gap, all variables on the right-hand side are past expectations of current values of aggregate inflation and changes in the output gap. While expectational terms in NKPC estimations are frequently replaced with ex-post values (e.g., Gali & Gertler, 1999), doing so in the SIPC would yield an error process that would be highly correlated with both regressors and instruments. It is thus critical to have actual measures of past forecasts as regressors. I address each of these points in turn.

Endogeneity, Instruments, and Truncation. Consistent estimation of the parameters of the SIPC requires an identification condition. Given that the current output gap is a right-hand-side variable, it will generally not be uncorrelated with the error term. Therefore, estimation of equation (1) by ordinary least squares or nonlinear least squares will be inconsistent. However, under the assumption of i.i.d. error terms, past information embodied in lagged values will be orthogonal to the error term, thereby justifying the estimation of equation (1) by instrumental variables.

Consider first a truncated version of (1),

$$\pi_t = \frac{(1 - \lambda)}{\lambda} \alpha x_t + (1 - \lambda) \times \sum_{j=0}^{J-1} \lambda^j F_{t-1-j}(\pi_t + \alpha \Delta x_t) + \varepsilon_t, \tag{2}$$

where I temporarily ignore the truncated subset of the SIPC. Under the assumption of i.i.d. error terms, one can use the orthogonality condition $E[\varepsilon_t Z_{t-1}] = 0$, where Z_{t-1} is a set of k variables dated $t - 1$ or earlier, to consistently estimate λ and α by nonlinear IV. Efficient estimation of these parameters requires a set of instruments that satisfy the orthogonality condition and are sufficiently correlated with the regressors of (2). Note that all past forecasts on the right-hand side of (2) are valid instruments, as are lags of the output gap. In the baseline estimation, I will use lags of the output gap and a subset of the past forecasts as instruments.

In practice, the truncation that must be imposed on the SIPC provides an additional source of error into equation (2). Specifically, equation (2) should be written as

[4] See Caballero (1989) and Reis (2006) for microfoundations of the SIPC based on firms facing fixed costs to acquiring information. Note that MR impose the additional assumption that professional forecasters have rational expectations.

[5] Deriving this is standard but requires the assumption that forecasters know and impose in generating their forecasts the equation describing the price level. Specifically it requires $F_t b_{t+1} = [F_t p_{t+1} - \gamma p_t]/(1 - \gamma)$, where b_t is the optimal reset price for firms.

[6] The error term can come from measurement error on the left-hand side or i.i.d. markup shocks.

[7] Hausman tests strongly support the notion that the output gap is correlated with the error term.

$$\pi_t = \frac{(1-\lambda)}{\lambda}\alpha x_t + (1-\lambda) \times \sum_{j=0}^{J-1} \lambda^j F_{t-1-j}(\pi_t + \alpha\Delta x_t) + \varepsilon_t + \nu_{t,t-J}, \qquad (2')$$

where $\nu_{t,j-J} = (1-\lambda)\sum_{j=J}^{\infty}\lambda^j F_{t-1-j}(\pi_t + \alpha\Delta x_i)$. Because this additional source of error is dated $t - J$ and earlier, the orthogonality condition will generally fail. However, consider the covariance of any variable z with $\nu_{t,t-j}$:

$$\mathrm{cov}(z, \nu_{t,t-J}) = (1-\lambda)\sum_{j=J}^{\infty}\lambda^j[\mathrm{cov}(z, F_{t-1-j}\pi_t + \alpha F_{t-1-j}\Delta x_t)].$$

This covariance will be nonzero unless z is uncorrelated with all forecasts dated $t - 1 - j\ \forall j \geq J$ of current inflation and changes in the output gap. However, because each covariance is weighted by $0 < \lambda^j < 1$, it follows that as the truncation point J rises, the covariance of any regressor with $\nu_{t,t-J}$ falls and will converge to 0 as J goes to infinity as long as the covariance of z with past expectations is not too explosive. Quantitatively, truncating past expectations should thus have little effect on the estimation for a large enough J. Monte Carlo exercises confirm that when the degree of information rigidity is low to moderate, we can consistently estimate α and λ even at low truncation points.[8] As the true value of λ rises, we require ever higher truncation points to consistently estimate λ and α. When the true level of information rigidity is $\lambda = 0.75$, so that firms update their information once a year on average, consistent estimation requires a truncation of approximately one year.

Forecast Measures. To separate the issue of price-setting decisions from the rationality of forecasts, I rely on historical measures of forecasts. The first approach is to use median expectations data from the Survey of Professional Forecasters (SPF).[9] The SPF data provide an ideal source of expectations because they are a direct measure of what economists were forecasting and are available on a quarterly basis.[10] Specifically, the SPF provides expected future paths for prices and real output over each of the subsequent four quarters from each vintage period. To generate expectations of changes in the output gap, I assume that forecasters knew the actual changes in the CBO measure of potential output and derive expectations of future changes in the output gap as expected changes in output minus actual changes in the CBO measure of potential output. The main limitation is that forecasts are provided for only the next four quarters.

As an alternative, I also generate forecasts for each quarter in a way designed to closely replicate what forecasters would have believed each time period. Specifically, for each quarterly observation (e.g., 1982:Q1), I follow Stock and Watson (2003) and run a set of bivariate VARs for both inflation and changes in the output gap with a set of predictive variables using real-time data available to agents at that time.[11] These are used to generate forecasts of future values of inflation and changes in the output gap from each set of VARs of that vintage, which are then averaged across (excluding the maximum and minimum forecasts).[12] I create lagged forecasts going as far as twelve periods earlier for each quarter from 1971:Q2 until 2004:Q2. For inflation forecasts, I use real-time data of inflation, unemployment, and changes in the output gap (though the CBO measure used in the output gap is not real time data), as well as the final series for the level of short-term interest rates, the interest rate spread (10 year minus 3 month T-bills), the second difference of oil prices, the first difference of industrial production index, and capacity utilization. Each VAR uses only the previous twenty years of data.[13] For forecasts of changes in the output gap, I replace oil prices with the first difference of M0. The lag length in each VAR is selected using the AIC.

B. *The New Keynesian Phillips Curve and Nonnested Model Tests*

The second criterion to assess the validity of the SIPC is whether it statistically outperforms alternative models of inflation dynamics. The natural alternative is the NKPC, which the SIPC was designed to replace. I first discuss the estimation procedure for the NKPC and then turn to the tests used to empirically differentiate between the two models.

New Keynesian Phillips Curve. The NKPC can be expressed as

$$\pi_t = \beta F_t \pi_{t+1} + \kappa x_t + \varepsilon_t, \qquad (3)$$

where β is the discount factor and κ is a function of both real rigidity and the degree of price stickiness. This relationship implies that current inflation is proportional to the current forecast of the present discounted sum of future output gaps. Because of the purely forward-looking nature of inflation, this model has been criticized on the grounds

[8] These are available from the author on request.

[9] SPF data are available at the Philadelphia Federal Reserve Board: http://www.phil.frb.org/econ/spf/index.html. Mean forecasts were also used and yielded qualitatively similar results.

[10] Other survey measures are not in an appropriate form for this type of analysis. Either they do not contain forecasts of future quarters one by one, or they do not yield precise estimates of future values of inflation and changes in the output gap.

[11] Real-time data were taken from Philadelphia Federal Reserve at http://www.phil.frb.org/econ/forecast/reaindex.html. See Croushore and Stark (2001) for a description.

[12] In addition, I impose that the AR forecast be one of the variables to be averaged over.

[13] Some series are not available over the whole sample. Additional forecasting variables are added as soon as twenty years' worth of data becomes available for that series.

that it overpredicts the speed at which inflation responds to monetary policy shocks. MR motivate the sticky information model as a direct substitute for the NKPC on the grounds that the sticky information model can address the failures of the NKPC. Knowing whether the SIPC outperforms the NKPC empirically is thus a particularly interesting question.

I propose to estimate the parameters of the NKPC in a manner consistent with that used for the SIPC. Namely, the measures of inflation expectations from the "Forecast Measures" section can be used as right-hand-side variables in estimating equation (3).[14] Under the assumption that ε_t is uncorrelated with all past information, equation (3) can be estimated by instrumental variables. Instruments used include a constant, three lags of the output gap, and the time $t - 1$ forecast of time $t + 1$ inflation.[15] Using SPF expectations, the GDP deflator for inflation, and the log deviation of output from the CBO measure of potential output for the output gap, estimation of (3) by instrumental variables from 1971:Q2 to 2004:Q2 yields

$$\pi_t = -0.38 + 1.12F_t\pi_{t+1} + 0.04x_t + \varepsilon_t$$
$$(0.26)\ (0.07) \qquad (0.02)$$

with Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Note that the coefficient on expected inflation is greater than, though not statistically different from, 1. The coefficient on the output gap is positive and statistically significant, as implied by the theory and noted in Adam and Padula (2003).[16]

Nonnested Model Tests. Because the SIPC and the NKPC are nonnested, I use two approaches to test the empirical validity of the SIPC relative to the sticky price alternative. First, I apply the Davidson-McKinnon (DM) J-test. This entails estimating each model augmented with the fitted value from the alternative model and testing the null that the coefficient on the fitted value of the alternative is 0. For example, under the null of the NKPC, we can estimate

$$\pi_t = \beta F_t\pi_{t+1} + \kappa x_t + \delta_{SI}\hat{\pi}_t^{SI} + \varepsilon_t, \tag{4}$$

where $\delta_{SI} = 0$ under the null of the NKPC and $\hat{\pi}_t^{SI}$ is the fitted value from estimating (2).[17] Similarly, we can test the null of the sticky information model using

$$\pi_t = \frac{(1-\lambda)}{\lambda}\alpha x_t + (1-\lambda) \times \sum_{j=0}^{J} \lambda^j F_{t-1-j}(\pi_t + \alpha\Delta x_t) + \delta_{SP}\hat{\pi}_t^{SP} + \varepsilon_t, \tag{5}$$

where $\hat{\pi}_t^{SP}$ is the fitted value from estimating (3) and $\delta_{SP} = 0$ is the null under the sticky information model.[18] Possible outcomes of the test include rejecting both models, rejecting neither, or rejecting one and not the other.[19]

As an alternative but closely related approach, I also consider an encompassing model test. Specifically, I estimate the following encompassing model,

$$\pi_t = \omega\pi_t^{SP}(\gamma, \kappa) + (1-\omega)\pi_t^{SI}(\lambda, \alpha) + \varepsilon_t, \tag{6}$$

where $\pi_t^{SP}(\gamma, k)$ is the NKPC of equation (3) and $\pi_t^{SI}(\lambda, \alpha)$ is the SIPC of equation (2).[20] Hence under this approach, I estimate the parameters of the two models jointly, along with the weighting parameter ω. Under the null of the sticky price model, we should have $\omega = 1$, while the null of sticky information is $\omega = 0$.[21] As with the DM tests, this approach can accept one model and reject the other, reject both, or fail to reject either.

III. Results

Inflation is measured using the implicit GDP price deflator. The output gap is measured as the annualized log deviation between real GDP and the CBO measure of potential output. I consider alternative measures of inflation and the output gap as robustness checks subsequently. All estimating equations include a constant.

[14] Roberts (1997) and Adam and Padula (2003) provide evidence that using survey measures of expectations of future inflation improves the empirical performance of the NKPC.

[15] While weak instruments are typically an issue in estimates of the NKPC, the use of expectations measures on the right-hand side mitigates this problem. One can strongly reject the null of weak instruments using the tests of Stock and Yogo (2004).

[16] Equivalent estimates using VAR-based expectations yield $\beta = 0.97$ (0.05) and $\kappa = 0.02$ (0.02). Newey-West standard errors allow serial correlation of four quarters. Almost identical results hold if labor's share is used instead of the output gap. Because much work has been done on estimating the NKPC, I will not report subsequent estimates of the NKPC unless these differ from those reported here.

[17] This is also estimated by IV using the same instruments as when estimating the NKPC with the addition of $F_{t-1}\pi_t$.

[18] In this case, instruments are the same as when estimating the SIPC plus one lag of inflation and $F_{t-1}\pi_{t+1}$.

[19] See Davidson and McKinnon (2002). Because these estimates are sometimes sensitive to initial values, I use two sets of initial values ($\delta_i = 0$ and $\delta_t = 1.0$) and present results from the one that achieves the lower value of objective function. The initial values used for other parameters are the estimated parameters from each Phillips curve.

[20] For the encompassing equation, I use all instruments from estimating the hybrid NKPC and SIPC.

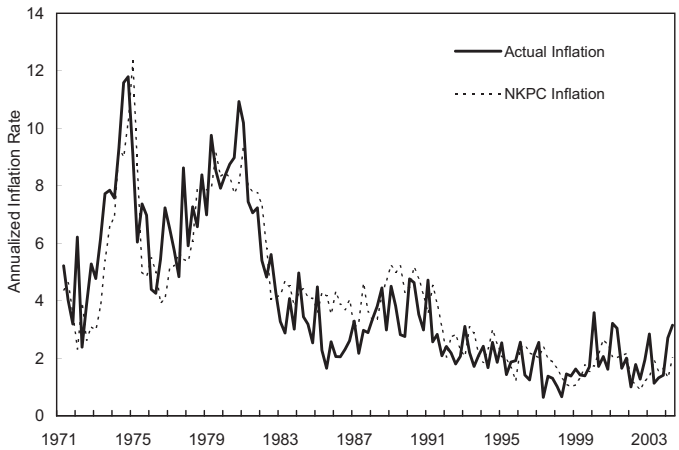
[21] Because this expression is highly nonlinear in five parameters, I estimate the parameters using a Markov chain Monte Carlo approach, following Chernozhukov and Hong (2003). I impose that $0 < \beta < 1$, $0 < \lambda < 1$, $0 < \omega < 1$, $\alpha > 0$, $\kappa > 0$. Starting values for the iterations are $\beta = 0.99$, $\lambda = 0.75$, $\alpha = 0.10$, $\kappa = 0.01$, and $\omega = 0.5$. I use 10,000 burn-in iterations and 100,000 subsequent iterations for the estimation. The standard deviation of shocks is taken from standard errors of parameter estimates from single-equation estimations, and set to 0.1 for ω. The objective function is that of nonlinear IV.

TABLE 1.—BASELINE ESTIMATES OF SIPC AND NONNESTED MODEL TESTS

	SPF	Real-Time VAR	
	$J = 4$	$J = 4$	$J = 12$
A: Estimates of Sticky Information Phillips Curve			
c	0.14 (0.22)	0.07 (0.22)	0.07 (0.23)
λ	−0.27 (0.21)	0.21 (0.23)	0.20 (0.22)
α	−0.01 (0.01)	0.02 (0.02)	0.01 (0.02)
B: Nonnested Model Tests			
δ_{si}	0.47* (0.28)	−0.37 (0.27)	−0.37 (0.27)
δ_{sp}	1.28*** (0.20)	1.20*** (0.22)	1.13*** (0.10)
ω	0.94*** (0.07)	0.97*** (0.03)	0.97*** (0.03)

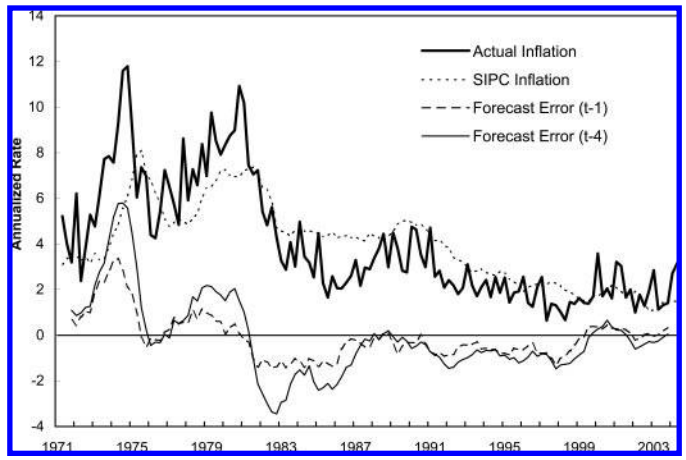
Note: SPF and real-time VAR refer to the source of forecasts used in each equation, c, λ, and α are the constant and degrees of information and real rigidity in the SIPC (equation (2)), respectively. δ_{si} and δ_{sp} are the coefficients on the fitted values of the SIPC and NKPC in equations (4) and (5), respectively, and ω is the weighting parameter in equation (6). J is the truncation used in estimates of the SIPC. All estimates done by nonlinear IV. See text for instruments. Standard errors in parentheses are Newey-West HAC allowing for four quarters of serial correlations. Statistical difference from 0 (and from 1 for ω).
*[2] significant at 10%; **[22] significant at 5%; ***[222]significant at 1%.

FIGURE 1.—PREDICTED INFLATION FROM NEW KEYNESIAN PHILLIPS CURVE



Note: Figure plots inflation and predicted inflation from the NKPC using expectations from VARs on real-time data and $c = 0$, $\beta = 0.99$, and $\kappa = 0.01$.

FIGURE 2.—PREDICTED INFLATION FROM THE STICKY INFORMATION PHILLIPS CURVE



Note: Figure plots inflation and predicted inflation from the SIPC using expectations from VARs on real-time data and $c = 0$, $\lambda = 0.75$, and $\alpha = 0.10$ with a truncation of $J = 12$. It also includes a four-quarter centered moving average of SPF forecast errors at the one- and four-quarter horizon.

A. *Baseline Results*

Table 1 presents estimates of the SIPC in (2), the DM tests of (4) and (5), and the encompassing model (6) on the full sample from 1971:Q2 until 2004:Q2 for different truncation points in the SIPC for the two measures of expectations. We look first at the results based on SPF forecasts, where the estimates of informational and real rigidities are both negative and insignificantly different from 0, contradicting the theoretical assumptions of the SIPC that both be positive. In addition, the SIPC is rejected under both nonnested model tests. The NKPC is not rejected by the encompassing model test and only weakly so using the DM test (at the 10% level). When the real-time VAR forecasts are used, the results are broadly similar regardless of the truncation used in the SIPC. Again, the estimates of both informational and nominal rigidities are insignificantly different from 0, though both are now positive. The nonnested model tests all reject the SIPC but fail to reject the NKPC. The evidence is thus unfavorable to the sticky information model along both sets of criteria considered. First, unlike the NKPC, the estimated structural parameters of the SIPC are inconsistent with an underlying sticky information model since we cannot reject the null that firms update their information every quarter. Second, the estimated SIPC is statistically inferior to the NKPC. Thus, by both metrics considered, the SIPC finds little support in the data.

To see why this may be, it is worthwhile examining the predicted values of the models. Figure 1 plots inflation and predicted inflation from the NKPC with $\beta = 0.99$ and $\kappa = 0.01$.[22] Overall, predicted inflation from the NKPC tracks actual inflation closely. It captures the two increases in inflation of the 1970s and early 1980s, but overpredicts inflation throughout the mid- to late 1980s. This version of the NKPC accounts for approximately 80% of the variation in inflation. Figure 2 plots actual inflation and that predicted by the SIPC using the real-time VAR forecasts with a truncation of three years with the parameter values proposed by MR: $\lambda = 0.75$ and $\alpha = 0.10$.[23] Predicted inflation from the SIPC accounts for a much smaller fraction of the variation in inflation, approximately 55%. In addition, this series differs from the time series of inflation along two

[22] $\kappa = 0.01$ is approximately equivalent to firms updating prices once a year on average with $\alpha = 0.10$.
[23] Constants are set to 0 for the NKPC and SIPC.

dimensions. First, predicted inflation fails to replicate the two inflation spikes of the 1970s and early 1980s and is also unable to reproduce the disinflation of the mid-1980s. I will refer to this as the *real-time forecast error* effect. Second, predicted inflation is much smoother than actual inflation. I will refer to this as the *inflation inertia* effect.

B. Real-Time Forecast Error Effect

The first effect is labeled the real-time forecast error effect because it reflects a feature specific to real-time forecasts of inflation: forecast errors are consistently too low in the 1970s, but too high in the 1980s and 1990s. Figure 2 illustrates this using a moving average (centered four-quarter) of SPF forecast errors at horizons of one and four quarters. During both inflationary episodes in the 1970s, forecast errors are positive, reflecting the fact that forecasters were caught off-guard by rising inflation rates. On the other hand, since the Volcker disinflation, professional forecasters have been consistently overestimating inflation. Both features are increasing in the forecasting horizon. The VAR forecasts based on the real-time data available to forecasters each quarter yield a very similar pattern.

This has important implications when estimating the parameters of the SIPC. In particular, a high value of λ in the SIPC places substantial weight on older forecasts of current inflation. This accounts for why predicted inflation, under the parameters of Mankiw and Reis, is lower than actual inflation in the 1970s but consistently higher than actual inflation in the 1980s and 1990s. Because the estimation seeks to minimize persistent departures between predicted and actual inflation, we get estimated values of λ that are close to 0; low values of λ shift the weight in the SIPC from old forecasts of current inflation to more recent forecasts of current inflation, which exhibit a less pronounced pattern of persistent forecast errors.

C. Inflation Inertia Effect

The inflation inertia effect refers to the excessive persistence and insufficient volatility of predicted inflation from the SIPC. To see this, suppose again we impose the preferred values of MR: $\lambda = 0.75$—firms update their information once a year on average—and $\alpha = 0.10$—a significant amount of real rigidity—on real-time VAR forecasts with a truncation of three years. The standard deviation of predicted inflation is 1.78. Actual inflation over the same time period had a standard deviation of 2.61, which implies that the SIPC underpredicts the volatility of inflation by over 30%. In addition, predicted inflation from the SIPC has an AR(1) coefficient of 0.999, whereas actual inflation has persistence of 0.88. For comparison, predicted inflation from the NKPC, assuming $\beta = 0.99$ and $\kappa = 0.01$, has a standard deviation of 2.35 and a persistence of 0.94.

The inflation inertia effect reflects the fact that the SIPC implies that inflation depends on a weighted average of past expectations of inflation. When there is a lot of information rigidity (λ is high), the SIPC places substantial weight on past expectations. This averaging across past expectations then filters out the volatility in past expectations, leaving only a smooth series in its wake. Note that this is another factor that pushes λ down in the estimation. With a low λ, most of the weight is placed on the most recent expectation and little on past forecasts. This eliminates the filtering process and enables the SIPC to more closely match the volatility and persistence of inflation. I return to the inflation inertia effect in section VB.

IV. Robustness

In this section, I investigate several issues that arise in the context of estimating sticky price and sticky information models. The first is the choice of series. I verify that my results are robust to using alternative measures of inflation as well as labor's share instead of the output gap, a point that has received much attention in the sticky price literature. Second, I consider the use of in-sample forecasts, as implicitly done in most other empirical work on the SIPC. Third, I redo the estimation while imposing a coefficient of real rigidity. Fourth, I examine the evidence for sticky information in the subperiod since 1984.

A. Robustness to Data Series

In the baseline estimation, the choice of the GDP deflator and the output gap (defined as the deviation of output from the CBO measure of potential) was based on limited availability of SPF forecasts for other series. In this section, I reproduce out-of-sample VAR forecasts for two alternative measures of inflation, as well as for the use of labor's share instead of the output gap. In each case, I generate forecasts from each quarter using the data preceding that date. I then replicate the estimation procedures outlined in section II. The results for a truncation of the SIPC of three years are presented in table 2.

With the nonfarm business (NFB) deflator as our measure of inflation, estimates of the degree of informational and real rigidities are small but positive and insignificantly different from 0, confirming the baseline results of table 1. The SIPC is again rejected according to both nonnested model tests. However, unlike the baseline results, the NKPC is also rejected by both nonnested model tests despite the fact that the estimated parameters of the NKPC (not shown) are nearly identical to those found previously. This rejection of the NKPC reflects the fact that the NKPC explains a smaller fraction of the variation in NFB inflation than GDP deflator inflation, with an R^2 of 0.70 rather than an improved performance of the SIPC. In particular, NFB inflation is more volatile than GDP deflator inflation, and expectations of future inflation are unable to account for this increased variation in inflation. With CPI inflation, the point estimate of information rigidity, at 0.40, is larger than in previous

TABLE 2.—ROBUSTNESS ANALYSIS

	Alternative Data Series			In-Sample Forecasts		Impose $\alpha = 0.1$		Post-1984	
	NFB	CPI	LS	$J = 4$	$J = 12$	SPF	VAR ($J = 12$)	SPF	VAR ($J = 12$)
A: Estimates of Sticky Information Phillips Curve									
c	0.19	0.17	−0.17	0.33***	0.27***	0.62***	0.20	0.41	0.81***
	(0.26)	(0.26)	(0.20)	(0.11)	(0.10)	(0.22)	(0.28)	(0.35)	(0.31)
λ	0.10	0.40*	0.17	0.37***	0.42***	0.52***	0.53***	0.75***	0.94***
	(0.23)	(0.20)	(0.20)	(0.12)	(0.13)	(0.06)	(0.06)	(0.07)	(0.01)
α	0.01	0.06	0.01	0.03	0.03	0.10	0.10	0.04	0.54
	(0.02)	(0.06)	(0.01)	(0.02)	(0.02)	n.a.	n.a.	(0.05)	(0.33)
B: Nonnested Model Tests									
δ_{si}	0.27**	0.30**	−0.34	0.28	0.27	0.14	−0.14	−0.08	−0.14
	(0.11)	(0.15)	(0.25)	(0.29)	(0.27)	(0.24)	(0.23)	(0.79)	(0.66)
δ_{sp}	0.95***	1.00***	1.31***	0.82***	0.98***	1.53***	1.15***	1.03***	0.97***
	(0.12)	(0.13)	(0.17)	(0.11)	(0.03)	(0.15)	(0.10)	(0.34)	(0.31)
ω	0.73***,aaa	0.72***,aaa	0.98***	0.93***	0.92***	0.95***	0.96***	0.79***	0.78***
	(0.05)	(0.05)	(0.02)	(0.07)	(0.08)	(0.03)	(0.03)	(0.15)	(0.16)

Note: NFB uses nonfarm business deflator series for inflation. CPI uses the consumer price index for inflation. Labor's share replaces the output gap as the forcing term in the Phillips curves. In each case under "Alternative Data Series," expectations are generated by VARs using data from these series and others as described in the "Forecast Measures" section of text. "In-Sample Forecasts" uses forecasts based on a single VAR estimated over the whole sample. c, λ, and α are the constant and degrees of information and real rigidity in the SIPC—equation (2) in text—respectively. Parameters δ_{si} and δ_{sp} are the coefficients on the fitted values of the SIPC and NKPC in equations (4) and (5), respectively, and ω is the weighting parameter in equation (6). All estimates done by nonlinear IV from 1971:Q2 to 2004:Q2, except for post-1984 estimates. See text for instruments. Standard errors in parentheses are Newey-West HAC allowing for four quarters of serial correlation. Statistical difference from 0 (and from one for ω) at the 10%, 5%, and 1% levels are denoted by a *(a), **(aa), and ***(aaa) respectively.

cases and is significantly different from 0 at the 10% level. The estimated coefficient of real rigidity remains insignificantly different from 0. However, the SIPC continues to be strongly rejected in the nonnested model tests. The NKPC is also rejected, reflecting the fact that CPI inflation is even more volatile than NFB inflation, and again this increased volatility is not sufficiently accounted for by expectations of future inflation.

I also consider the use of labor's share as the relevant forcing variable in each Phillips curve. Gali and Gertler (1999) argue that labor's share is a better measure to use than the output gap since it is more closely tied to marginal costs. The use of labor's share in the estimation of the two Phillips curves has little effect on the estimation results here. The estimated degrees of informational and real rigidities are insignificantly different from 0. The nonnested model tests continue to strongly reject the SIPC but fail to reject the NKPC. Thus, the use of labor's share does not qualitatively change any of the results relative to the baseline estimation.

B. *In-Sample Versus Out-of-Sample Forecasts*

Previous work on the empirical validity of the SIPC has typically not rejected the SIPC on structural grounds, with most finding estimated levels of information rigidity consistent with firms updating their information between once and twice a year. A key difference between the approach used here and this previous work is the nature of the forecasts used. Rather than relying on real-time forecasts, previous authors have relied on a single VAR estimated over the whole period to generate expectations.[24] Such an approach, by construction, eliminates the real-time forecast error effect since forecast errors in the VAR must be i.i.d. To see that this is important for the estimation, I construct an alternative set of forecasts using a single VAR with inflation and changes in the output gap estimated over the whole sample.[25] I then use the VAR coefficients to generate forecasts from each time period. The baseline estimation, using these in-sample forecasts, is redone, and the results are presented in table 2. Note that the estimated levels of information rigidity are now positive and statistically significant, implying that firms update their information a little over twice a year on average. However, the estimated degree of real rigidity remains insignificantly different from 0, and the nonnested model tests continue to strongly reject the null of the SIPC but fail to reject the null of the NKPC.[26]

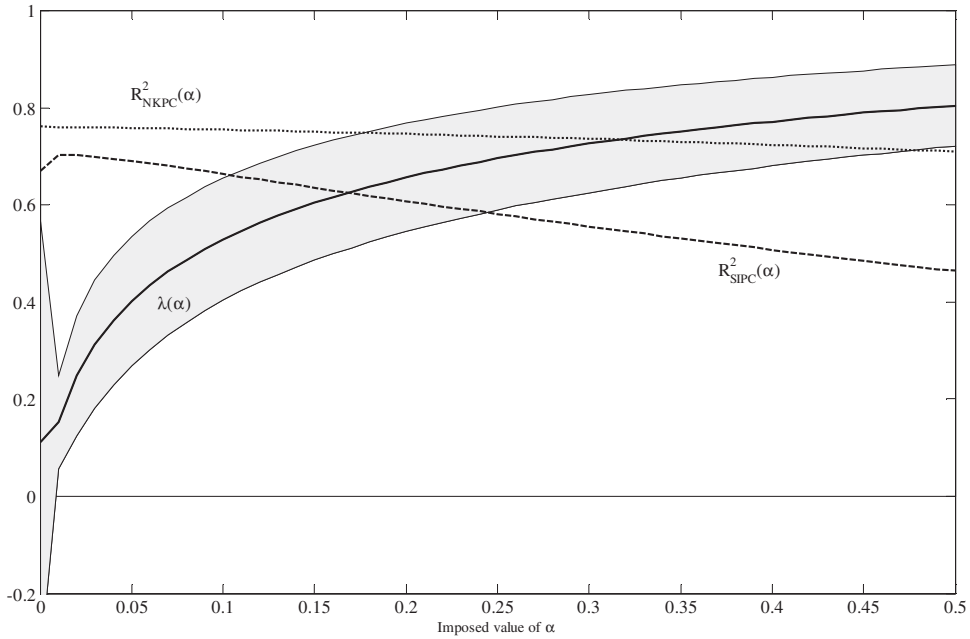
This alternative set of forecasts illustrates the importance of the real-time forecast error effect. By construction, in-sample VAR forecasts eliminate the real-time forecast error effect. Yet the real-time beliefs of forecasters differed substantially from what they would have forecast had they had access to information from future values. Since the key idea behind sticky information is that inflation depends largely on agents' beliefs about the current state, the use of historical forecasts is more appropriate given the very different patterns exhibited by in-sample forecasts over the same time period. One should also note that the inflation inertia effect is present regardless of whether in-sample or out-of-sample forecasts are used. With in-sample forecasts, the standard deviation of predicted inflation from the SIPC under the

[24] See Dupor et al. (forthcoming), Kiley (2007), and Korenok et al. (2007). Note that these authors estimate the VAR and the SIPC jointly, thereby imposing the cross-equation restrictions implied by the rational expectations solution. Khan and Zhu (2006) is an exception as they rely on out-of-sample forecasts.

[25] The VAR is estimated from 1967:Q1 to 2004:Q2. Lag length is chosen using the AIC.

[26] For the NKPC, the results are largely unchanged. The estimated β is 1.01 (0.01), and the estimate of κ is 0.008 (0.003).

FIGURE 3.—ESTIMATED LEVELS OF INFORMATION RIGIDITY, CONDITIONAL ON THE DEGREE OF REAL RIGIDITY



Note: The figure displays estimated levels of information rigidity (λ) for different imposed values of real rigidity (α) when estimating the SIPC. The figure also displays the implied R^2 for the SIPC for each value of λ, as well as the corresponding R^2 from the estimated NKPC.

assumed parameters of MR is 25% less than that of actual inflation.

C. *Imposing the Degree of Real Rigidity*

In this section, I consider the implications of imposing a degree of real rigidity in the estimation of the SIPC as a way of more precisely estimating the degree of information rigidity.[27] In particular, I focus on the case of $\alpha = 0.10$, the value assumed by MR. Low values of α imply substantial strategic complementarities in price setting among firms and are necessary for the sticky information model to deliver a delayed response of inflation to monetary policy shocks.[28] In addition, because substantial amounts of real rigidity are necessary for sticky price models to match the persistence in the data, imposing this value does not bias, ex ante, the exercise in favor of either model.[29] For the NKPC and SIPC to have identical degrees of freedom, I also restrict the coefficient on the output gap in the NKPC to be $\kappa = 0.01$. Note that the latter is equivalent to imposing $\alpha = 0.10$, and firms update prices approximately once a year on average. These values are also imposed in each nonnested model test.

The results are also presented in table 2. Note that the estimated levels of information rigidity are now 0.52 and 0.53 for SPF and real-time VAR (truncation of three years) forecasts, respectively, and are significantly different from 0 at the 1% level. However, the nonnested model tests again reject the null of the SIPC but fail to reject the NKPC. Thus, while the SIPC continues to fare poorly on statistical grounds, it appears to fare better on structural grounds, according to the first criterion. The reason that estimates of information rigidity are higher with this imposed value of α is as follows. In the unrestricted case, the estimate of λ must be close to 0 to minimize both the real-time forecast error and the inertia effects. But the data imply a small and positive link between inflation and the output gap, as seen in the estimates of the NKPC. Note that the coefficient on the output gap term in the SIPC is $(1 - \lambda)\alpha/\lambda$. If the estimate of λ must be close to 0, then α must be small as well to avoid having a large coefficient on the output gap. This is what occurs in the unrestricted estimation. But when α is imposed to be greater than its unrestricted estimated value, this magnifies the coefficient on the output gap. To offset this effect requires higher estimated values of λ.

To illustrate this effect more clearly, I reproduce estimates of the degree of information rigidity for levels of α between 0 and 0.5. Parameter estimates and standard errors are shown in figure 3. Note that estimates of λ are rising monotonically with α, consistent with the explanation above. However, as the estimated degree of information rigidity rises, the real-time forecast error and inflation inertia effects become increasingly present, and the empirical fit of the model declines. This is illustrated by the fact that the R^2 of the SIPC is rapidly declining in α. Interestingly, this is not the case for the NKPC, for which the empirical fit is

[27] I am grateful to an anonymous referee for this suggestion.
[28] See Coibion (2006).
[29] Woodford (2003) argues that plausible values of α are between 0.10 and 0.15.

much more robust to the assumed value of α.[30] Figure 3 illustrates this by showing the implied R^2 of predicted inflation from the NKPC with imposed values of κ. Essentially there is an empirical trade-off between the two criteria for assessing the SIPC: when we impose values of α that yield levels of information rigidity consistent with a delayed response of inflation to monetary policy shocks, the statistical fit of the SIPC worsens substantially relative to the NKPC, reflecting the real-time forecast error and inflation inertia effects.

D. Subsample Estimates

One could argue that applying the SIPC to the 1970s is expecting too much of the model. Since this was a period of volatile output and inflation, in which these economic variables were much in the news, the time-dependent process underlying the sticky information model may be a particularly poor assumption (though the same could potentially be said for the sticky price model). In addition, Khan and Zhu (2006) perform a similar analysis for the SIPC and find plausible and statistically significant values of λ, but their estimates are from 1980:Q1 on. To see whether the time sample is important, table 2 presents results from replicating the baseline estimation since the first quarter of 1984. The post-1984 period is frequently referred to as the "great moderation," in which the volatility of output and inflation is greatly reduced relative to the previous period. As such, it is a natural break point to impose.[31]

Note first that the estimated levels of information rigidity differ from those over the whole time period. Point estimates of the degree of information rigidity are all statistically positive and relatively high. With SPF forecasts, λ is estimated to be 0.75, exactly the value assumed by MR. Real-time VAR forecasts point to higher levels of information rigidity, reaching 0.94 at a truncation of twelve quarters. Note that $\lambda = 0.94$ implies that firms update their information once every four years on average. The estimated levels α remain insignificantly different from 0 in each case. The nonnested model tests again reject the SIPC but fail to reject the NKPC. However, the point estimates of ω imply that a larger weight is now placed on the SIPC than was the case over the whole sample, implying that its empirical fit has improved relative to that of the NKPC over this subsample period. Nonetheless, we cannot reject that $\omega = 1$ but can strongly reject the null of $\omega = 0$.

Overall, the sticky information model clearly performs better over this subsample period along one dimension: estimates of the degree of information rigidity are now significantly different from 0. However, the fact that α remains insignificantly different from 0 implies that it is still difficult to find any strong link between the nominal and real side of the economy when conditioning on past forecasts of the current state. In addition, the sticky information model continues to be strongly rejected against the alternative of the basic sticky price model using nonnested model tests, confirming that statistically, the SIPC is outperformed by the simple sticky price model it was designed to replace.

V. Discussion

In this section, I delve more deeply into two puzzling results presented in the paper. The first is the difference in the estimated levels of information rigidity over the whole sample and since the 1980s. The second is the inflation inertia effect: why predicted inflation from the SIPC under the parameters of Mankiw and Reis appears to be so much more inertial than actual inflation.

A. Subsample Estimates of Information Rigidity and Rationality of Forecasts

The most striking feature of the subsample estimates is the high estimated degrees of information rigidity. These stand in sharp contrast to those found over the whole sample, which were low and not statistically different from 0. While the estimate of α remains insignificantly different from 0 and the nonnested model tests are consistent across periods, the large difference across periods in estimated degrees of information rigidity appears puzzling. In this section, I argue that this subsample difference arises because persistent forecast errors on the part of professional forecasters can give the appearance of sticky information in price-setting decisions, even in the absence of sticky information on the part of firms.

There is a large literature on the rationality of survey measures of inflation expectations, the principal result of which has been that inflation forecasts often appear to be rational in the long run but not the short run.[32] To verify this, I perform the following test of the rationality of the forecasts used in the estimation of the SIPC,

$$\pi_t - F_{t-1}\pi_t = c + \psi F_{t-j}\pi_t + \varepsilon_t, \tag{7}$$

for different lagged expectations.[33] The resulting values of $\hat{\psi}$, along with 95% confidence intervals, are presented in figure 4 for SPF and real-time VAR forecasts. The key issue here is whether forecast errors are predictable using older forecasts. The results confirm previous findings that forecasts appear to be consistent with rationality in the long run

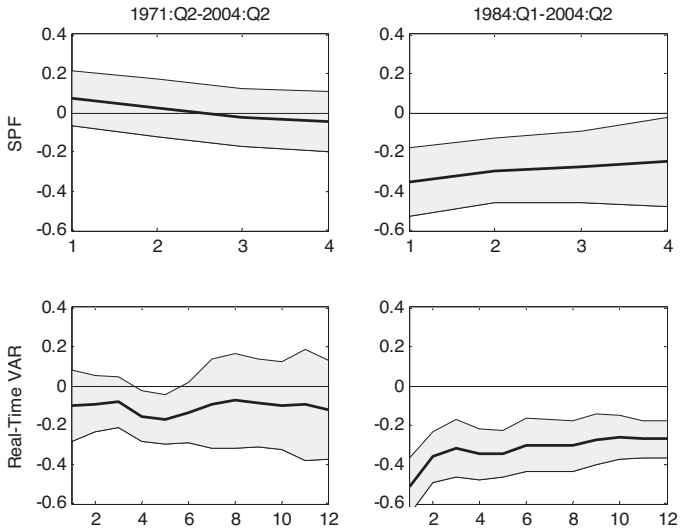
[30] This is due to the fact that a change in α has a smaller effect on the coefficient on the output gap in the NKPC than in the SIPC, when one assumes identical degrees of price stickiness and sticky information.

[31] See McConnell and Perez-Quiros (2000). The results are qualitatively unchanged for different break points from the early to mid-1980s.

[32] See Croushore (1998) and Roberts (1998) for evidence and a survey of this literature, respectively.

[33] Under the null of rational expectations, Working (1960) shows that the error term in equation (10) is MA(1). Hence, for $j = 1$, I estimate equation (10) by IV using a constant and three lags of inflation as instruments. For $j > 1$, the right-hand-side variables are orthogonal to the error term, and OLS is consistent. Newey-West HAC standard errors are calculated using a truncation equal to $j + 1$ to take into account overlapping observations.

FIGURE 4.—TESTS OF RATIONALITY OF REAL-TIME INFLATION FORECASTS



Note: The figure presents estimates of $\hat{\psi}$ from the regression $\pi_t - F_{t-1}\pi_t = c + \psi F_{t-j}\pi_t + \varepsilon_t$, for SPF and real-time VAR forecasts over different samples with 95% confidence intervals. Standard errors are Newey-West HAC allowing for serial correlation of order $j + 1$. The horizontal axis denotes the timing (lag) of the expectation on the right-hand side.

(at least according to this test) but not in the short run. Over the whole sample, there is little evidence that forecast errors of inflation are predictable using old forecasts. However, since the early 1980s, forecast errors have been highly predictable, even using very outdated forecasts. The latter is due to the pattern of falling inflation over this time period, which has left professional forecasters consistently overestimating inflation. The result, as could be seen in figure 2, is a period in which forecast errors are persistent and highly predictable.[34]

Because the SIPC relates current inflation to past forecasts of inflation, periods with predictable and persistent forecast errors could lead to nonzero estimates of λ, even in the absence of delayed information acquisition by price setters. To assess whether this pattern of predictable forecast errors is sufficient to explain the difference between subsample estimated values of λ, I consider a Monte Carlo exercise in which firms face no costs to acquiring new forecasts. Specifically, I assume that firms face sticky prices but not sticky information, so that the NKPC holds, conditional on professional forecasts. The main components of the model closely follow Erceg and Levin (2003):

$$\pi_t = \beta\tilde{\mathbb{E}}_t\pi_{t+1} + \kappa x_t + \varepsilon_t^{\pi} \tag{8}$$

$$x_t = \theta\tilde{\mathbb{E}}_t x_{t+1} + (1 - \theta)x_{t-1} - (i_t - \tilde{\mathbb{E}}_t\pi_{t+1}) \tag{9}$$

$$i_t = \rho i_{t-1} + (1 - \rho)[\phi_{\pi}(\pi_t - \pi_t^*) + \phi_{\Delta y}\Delta y_t], \tag{10}$$

where (8) is the NKPC conditional on expected inflation, (9) is the Euler equation for the output gap x_t conditional on expectations of the future output gap and the real interest rate, and (10) is a Taylor rule describing interest rate decisions by the central bank. The Taylor rule implies that the central bank responds to deviations of inflation from a stochastic target rate π_t^*. The target rate is observable by forecasters, but its components are not. The target rate follows:

$$\pi_t^* = \pi_t^p + \varepsilon_t^q, \tag{11}$$

where ε_t^q is an i.i.d. shock and π_t^p follows an AR(1) process with persistence parameter ρ_p. Forecasters use a Kalman filter to generate optimal forecasts of inflation, the inflation target, and the output gap conditional on the observable variables and the known structure of the model. These expectations are denoted by $\tilde{\mathbb{E}}_t$.

To generate a pattern of forecast errors similar to that observed in U.S. data, the shocks to the permanent component of the inflation target are chosen so that the permanent component of target inflation in each simulation is equal to U.S. HP-filtered inflation over the whole sample. This ensures an upward trend in inflation in the 1970s followed by a gradual disinflation in the 1980s and 1990s. The other shocks in the model are assumed to be normally distributed.[35] The model is simulated 10,000 times, with each simulation having a burn-in period of 45 quarters followed by 133 periods approximating the period from 1971:Q2 to 2004:Q2.[36] The standard deviation of i.i.d. shocks to the NKPC is set equal to the standard deviation of the observed residuals from the NKPC (0.0027). The natural level of output follows an AR(1) process with persistence of $\rho_n = 0.99$ and i.i.d. shocks with standard deviation of 0.007.

This approach, on average, replicates the qualitative patterns of forecast error bias and predictability in each subsample, as well as over the whole period. Given these generated data, I estimate the SIPC in the same way as done in the empirical analysis with a truncation $J = 4$ and $J = 12$ over the whole sample and the post-1984 equivalent period using $\tilde{\mathbb{E}}_t$ as the measure of forecasts. Mean estimates of the degree of information rigidity from 10,000 simulations are presented in table 3. First, the median estimated level of information rigidity over the whole sample is close to 0, as found in the baseline results. This follows from the fact that there is no sticky information in the model and that forecast errors are unpredictable on average over the whole period, as in the data. Median estimates of α are also quite small, as observed in the baseline results. Second, the mean estimate of λ in the subsample period is high: 0.60 on

[34] Note that predictable forecast errors do not necessarily imply that forecasters are irrational. For example, they could be setting forecasts optimally conditional on limited information about the state of the economy or uncertainty about the goals (or credibility) of monetary policymakers.

[35] I set the standard deviation of i.i.d. shocks to the inflation target equal to 0.002.

[36] I set $\beta = 0.99$, $\kappa = 0.01$, $\theta = 0.5$, and $\rho = 0.90$. Following Erceg and Levin (2003), I set the Kalman gain parameter equal to 0.13 and $\rho_p = 0.999$. The standard deviation of temporary shocks to the inflation target is set to 0.002.

TABLE 3.—ESTIMATING THE SIPC IN THE ABSENCE OF STICKY INFORMATION

	Whole Sample		Subsample	
	$J = 4$	$J = 12$	$J = 4$	$J = 12$
λ	−0.06	−0.08	0.60	0.82
	(0.29)	(0.12)	(0.35)	(0.18)
α	0.00	0.00	0.04	0.33
	(0.02)	(0.01)	(0.03)	(0.14)

Note: The table presents mean estimates of the degree of information rigidity (λ) in the SIPC when the true model has sticky prices but no sticky information, and forecast errors replicate, on average, those in the data. See section VA for details. J is the truncation applied to the SIPC in the estimation. Results come from 10,000 simulations of 133 periods each. Standard deviations of parameter estimates are in parentheses. The subsample period is equivalent to post-1984 estimates in previous sections.

average using a truncation of one year and 0.82 with a truncation of three years. The mean estimated α is also increasing in the estimated level of λ, as observed in the empirical results.

This exercise illustrates how the gradual adjustment of forecasts, here due to imperfect information, can mistakenly lead one to conclude that sticky information is an important component of price-setting decisions. The presence of predictable forecast errors since the 1980s can account for what appear to be high estimated levels of information rigidity over this time period, even though firms are continually acquiring updating forecasts. Of course, the presence of predictable forecast errors points to the potential importance of informational rigidities on the part of professional forecasters. Whether these should be modeled as sticky information agents as argued by Mankiw et al. (2003) or as agents who imperfectly observe the current state, as done in Erceg and Levin (2003), is an open question.[37] One advantage of the limited information approach used in this paper is to be able to focus on the price and information decisions firms make without having to take a stand on the model that applies to forecasters.

B. *Inflation Inertia Effect*

A striking feature of predicted inflation from the SIPC under the parameters of Mankiw and Reis is that it is much more inertial than either actual inflation or predicted inflation from the sticky price model. This result, which is largely independent of whether in-sample or out-of-sample forecasts are used, is particularly surprising because the sticky information model was designed specifically to match the inflation inertia observed in response to monetary shocks that sticky price models could not replicate. Mankiw and Reis explicitly argue that this is the key empirical fact that is hard to match. Their model, with a sufficient combination of informational and real rigidities, is successful at matching this fact. Yet empirically, with this same combination of informational and real rigidities, it appears to do a worse job of matching the aggregate unconditional time-series properties of inflation than the model it was designed to replace.

To see how this dichotomy could exist, consider the pattern of responses to identified monetary policy shocks as typically observed in the empirical literature: interest rates adjust rapidly, the response of output peaks after approximately six months, but the peak response of inflation does not occur until one to two years after the shock.[38] Now suppose that there were no other shocks in the economy or that other shocks yielded a similar pattern of responses; then in the aggregate data, inflation would tend to lag other macroeconomic variables, particularly interest rates and output. Table 4 presents cross-correlations of inflation with other macroeconomic variables from 1971:Q2 to 2004:Q2. Note first that the peak correlation (in absolute value) between inflation and output growth is contemporaneous. However, the correlation between current inflation and future values of output growth is greater than the correlation between current inflation and lagged values of inflation. Clearly inflation does not lag output growth. With respect to labor's share, the peak correlation is also contemporaneous, and correlations with leads and lags are highly symmetric, indicating little evidence of inflation leading or lagging labor's share. With respect to the output gap and unemployment, inflation is most highly correlated with future values of these variables, indicating that it strongly leads. A similar pattern holds with respect to both short- and long-term interest rates: inflation leads these variables. Overall, inflation does not appear to be a lagging indicator.

The fact that the lead-lag patterns observed after monetary policy shocks differ substantially from those in the aggregate data need not be surprising. Empirical work typically finds that monetary policy shocks do not explain

[37] Coibion and Gorodnichenko (2008b) study the response of forecast errors and disagreement among forecasters after identified structural shocks and find that professional forecasters respond in a manner more consistent with imperfect information than sticky information.

[38] See Christiano et al. (1999).

TABLE 4.—CROSS-CORRELATION OF INFLATION WITH OTHER MACROECONOMIC VARIABLES

	$\rho(\pi_t, X_{t+j})$																
	−8	−7	−6	−5	−4	−3	−2	−1	0	1	2	3	4	5	6	7	8
GDP growth	0.07	0.09	0.05	0.01	0.01	−0.10	−0.16	−0.18	**−0.22**	−0.21	−0.19	−0.21	−0.20	−0.13	−0.09	−0.05	−0.08
Labor's share	0.39	0.40	0.43	0.49	0.53	0.56	0.59	0.62	**0.63**	0.60	0.56	0.54	0.53	0.52	0.49	0.46	0.46
Unemployment rate	0.07	0.07	0.07	0.07	0.07	0.10	0.15	0.19	0.26	0.34	0.42	0.50	0.57	0.62	0.67	0.72	**0.75**
GDP gap	0.04	0.08	0.10	0.11	0.12	0.08	0.02	−0.04	−0.12	−0.20	−0.27	−0.35	−0.42	−0.48	−0.52	−0.55	**−0.59**
3-month T-bills	0.07	0.13	0.20	0.29	0.37	0.43	0.49	0.55	0.59	0.61	**0.63**	**0.63**	0.61	0.60	0.58	0.56	0.56
10-year bonds	−0.01	0.04	0.09	0.14	0.20	0.26	0.32	0.38	0.44	0.50	0.55	0.59	0.60	0.62	**0.63**	**0.63**	**0.63**

Note: The table presents the correlation between inflation at time t and each variable at time $t + j$, where j is given by the numbers at the top of the table. The values in bold indicate the timing of the highest correlation (in absolute value) between inflation and that variable. All correlations are done from 1971:Q2 until 2004:Q2.

much of the variation in inflation: Andres, Lopez-Salido, and Nelson (2005) find that monetary policy shocks account for approximately 10% of the variance in inflation, Coibion and Gorodnichenko (2008a) find less than 10%, and Altig et al.'s (2005) results point to 14% of the variance of inflation being accounted for by monetary policy shocks.[39] Second, other identified shocks appear to yield more rapid responses of inflation. In particular, recent work on identifying technology shocks through long-run restrictions has uncovered that inflation appears to respond most strongly on impact.[40] In addition, variance decompositions indicate that technology shocks account for up to 50% of the variance in inflation. The fact that aggregate inflation does not appear to lag other macroeconomic variables could thus just be a reflection of the small fraction of the inflation variance accounted for by monetary policy shocks and the fact that other more quantitatively important shocks yield a more rapid response of inflation.

This has important implications when estimating models based on aggregate data that inherits these features. The sticky information model, while able to match the response to monetary shocks, does so by building in inflation inertia. This also tends to produce a delayed response of inflation to other shocks, including technology shocks (see Trabandt, 2005). Because these seem to account for a much greater fraction of the variance of inflation than monetary policy shocks, the SIPC is strongly rejected when tested using aggregate unconditional data. The sticky price model, on the other hand, builds in forward-looking inflation. This can readily replicate the response of inflation to technology shocks but not monetary policy shocks. However, because the latter account for a smaller fraction of the variance in inflation, the NKPC fares better in the data.

The implication is that the delayed response of inflation to monetary policy shocks is only one piece of the puzzle. The other piece is that inflation overall is not a lagging indicator. Matching both sets of facts requires a model that can predict a rapid response of inflation to certain shocks, like technology shocks, and a gradual response of inflation to policy shocks.[41] This issue is not limited to the basic sticky price and sticky information models. For example, Trabandt (2005) shows that a hybrid sticky price model that can replicate the delayed response of inflation to monetary policy shocks also implies a delayed response of inflation to technology shocks. Altig et al. (2005) estimate a sticky wage model with indexation by minimizing the distance between the model's predicted responses for macroeconomic variables and those observed in the data in response to identified monetary policy and technology shocks. Their estimates imply significant indexation of wages, allowing them to match the delayed response of inflation to monetary policy shocks. However, their model then counterfactually predicts a delayed response of inflation to technology shocks. Edge, Laubach, and Williams (2003) pursue a similar exercise but reach the opposite conclusion: they find little evidence for indexation of wages. Their model matches the rapid response of inflation to identified technology shocks but is then unable to match the delayed response of inflation to monetary policy shocks. This differentiated response of inflation to shocks in the data implies that models with standard mechanisms for inducing inflation inertia are unlikely to be able to replicate both sets of facts jointly.

VI. Conclusion

Mankiw and Reis (2002) argue that the sticky information model, in which firms acquire new information infrequently but update prices continuously, should replace the sticky price model, in which firms acquire information continuously but change prices infrequently, as the workhorse model of monetary economics. Their primary motivation is that, unlike the sticky price model, the sticky information model can replicate a key stylized fact: monetary policy shocks have a delayed effect on inflation. I show that empirically the sticky price model strongly dominates the sticky information model conditional on historical inflation forecasts. There are two primary sources for this result. First, real-time inflation forecasts are consistently too low in the 1970s but too high since the 1980s, particularly at long horizons. The sticky information model, based on parameters that enable it to match the delayed response of inflation to monetary policy shocks, places significant weight on older forecasts and therefore underpredicts inflation in the 1970s but overpredicts it since the 1980s. Second, the sticky information model predicts excessive smoothness in inflation and that inflation should lag other macroeconomic variables. I argue that in the data, inflation is not a lagging indicator, which reflects the fact that some nonmonetary policy shocks predict rapid adjustment of inflation. The sticky information model, which builds in a delayed response of inflation to shocks, is thus unable to match this important element in the data and, as a result, fares poorly empirically.

There is a strong symmetry in the weaknesses of the two models. The literature has long emphasized the inability of the basic sticky price model to predict gradual responses of inflation to monetary policy shocks. However, recent work has also demonstrated that in response to technology shocks, inflation adjusts rapidly. The sticky price model can naturally replicate this feature. The sticky information model, on the other hand, can reproduce the delayed response of inflation to monetary policy shocks but is then unable to match the rapid response of inflation to technology shocks. Because aggregate data indicate that inflation fails to lag other macroeconomic variables, shocks that yield

[39] See also Leeper, Sims, and Zha (1996) and Christiano et al. (1999) for similar results for the price level.

[40] See Gali (1999), Christiano, Eichenbaum, and Vigfusson (2003), Edge, Laubach, and Williams (2003), and Dupor, Han, and Tsai (2009).

[41] This point is emphasized in Dupor et al (2009).

rapid adjustment of inflation explain much of the variance in inflation. It should thus not be surprising ex post to see the NKPC dominate the SIPC empirically.

The key implication is that a successful model must be able to match both sets of facts: rapid adjustment of inflation to technology (and possibly other) shocks, as well as a delayed response of inflation to monetary policy shocks. Reconciling the two facts will likely require elements of both price stickiness and informational frictions. The fact that the NKPC does so well empirically when estimated conditional on historical inflation forecasts points to the need to model both price and informational rigidities.[42] For example, in the model of Erceg and Levin (2003) used in the Monte Carlo exercise, the presence of uncertainty about the monetary policy target induces agents to slowly adjust their forecasts about future inflation after a permanent shock to the inflation target, causing inflation to respond more slowly than in a full-information environment. Yet the fact that technology is observable yields a rapid adjustment of inflation to productivity shocks.[43] Alternatively, one could model a menu cost environment in which firms observe their inputs and productivity perfectly but face idiosyncratic unobservable shocks to their demand. In such an environment, inflation will respond rapidly to productivity shocks but slowly to demand shocks since firms will seek to delay paying the menu cost until they are sufficiently confident that a persistent aggregate demand shock has occurred. Making further progress on modeling inflation dynamics is likely to require more refined approaches to modeling the interaction of price-setting decisions with information acquisition and diffusion processes across the population.

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[43] See Mackowiak and Wiederholt (2009). See also Gorodnichenko (2008) for an example of menu costs and imperfect information jointly implying a delayed response of inflation to demand shocks.

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