How Robust Are Popular Models of Nominal Frictions?

Benjamin D. Keen and Evan F. Koenig

Research Department

Working Paper 0903

Federal Reserve Bank of Dallas

How Robust are Popular Models of Nominal Frictions?*

Benjamin D. Keen†
University of Oklahoma

Evan F. Koenig‡
Federal Reserve Bank of Dallas

This Draft: September 2009

Abstract

This paper analyzes three popular models of nominal price and wage frictions to determine which best fits post-war U.S. data. We construct a dynamic stochastic general equilibrium (DSGE) model and use maximum likelihood to estimate each model's parameters. Because previous research finds that the conduct of monetary policy and the behavior of inflation changed in the early 1980s, we examine two distinct sample periods. Using a Bayesian, pseudo-odds measure as a means for comparison, a sticky price and wage model with dynamic indexation best fits the data in the early-sample period, whereas either a sticky price and wage model with static indexation or a sticky information model best fits the data in the late-sample period. Our results suggest that price- and wage-setting behavior may be sensitive to changes in the monetary policy regime. If true, the evaluation of alternative monetary policy rules may be even more complicated than previously believed.

JEL Classification: C51; E31; E32; E52.
Keywords: Sticky prices; Sticky wages; Sticky information.

---

*We would like to thank Nathan Balke and Kevin Lansing for helpful discussions and comments. We are also grateful to Pengfei Wang and Yi Wen for supplying us the code underlying Wang and Wen (2006). The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

†Benjamin D. Keen, Department of Economics, University of Oklahoma, 729 Elm Ave., 329 Hester Hall, Norman, OK 73019. Tel: (405) 325-5900. Fax: (405) 325-5842. E-mail: ben.keen@ou.edu.

‡Evan F. Koenig, Research Department, Federal Reserve Bank of Dallas, 2200 N. Pearl St., Dallas, TX 75201. Tel: (214) 922-5156. Fax: (214) 922-5194. E-mail: Evan.F.Koenig@dal.frb.org.

1 Introduction

1.1 Motivation and Main Results

Economists have recently had considerable success constructing and estimating dynamic stochastic general equilibrium (DSGE) models that are competitive with vector autoregressive (VAR) models in their ability to match macroeconomic data.[1] Because they are grounded in utility and profit maximization, DSGE models are potentially robust to changes in the conduct of policy, which is a feature that makes them attractive to policy analysts. This robustness assumes that the utility and profit maximization problems underlying the DSGE model are correctly specified [Del Negro et al. (2007)]. In this paper, we present evidence that the price- and wage-setting assumptions embedded in many DSGE models that are used for macroeconomic policy analysis are too restrictive. Specifically, the data suggest that past changes in the economic and policy environment have led to shifts in price- and wage-setting behavior that many DSGE models fail to capture.

DSGE models require a mix of nominal and real rigidities in order to generate realistic impulse responses and autocorrelations.[2] Although the presence of real frictions is fairly noncontroversial, the existence and specific form of nominal frictions has generated much debate. Motivated by the "menu costs" literature, early DSGE models held prices fixed between discrete price readjustment opportunities. In pursuit of plausible qualitative and quantitative results, however, many researchers have now dropped that assumption. Instead, these researchers assume that all prices change every period, but not every price is reoptimized each period. In a sticky price and wage framework, prices and wages which are not reoptimized increase automatically by the steady-state price and wage inflation rates (static indexation) or by the lagged price and wage inflation rates (dynamic indexation), respectively. In the "sticky information" approach, firms and households choose price and wage paths in advance and follow those paths until the next optimization opportunity.

Each of these price-adjustment mechanisms is appealing under certain circumstances. Adjusting by a constant default inflation rate is reasonable in a stable-inflation environment; indexing to lagged aggregate inflation is a plausible strategy when inflation movements are unpredictable and highly persistent; while presetting price and wage paths is appealing when inflation is volatile but predictable. This line of reasoning suggests that changes in the conduct of monetary policy and/or changes to the stochastic processes of exogenous disturbances might alter the method in which prices and wages are set. DSGE models, however, typically do not allow for shifts in price- and wage-setting behavior. As a result, these models may be nothing more than local approximations which are reliable only in a specific economic environment.

We examine the robustness of alternative DSGE models by comparing their per-

[1] See, for example, Smets and Wouters (2003) and Christiano, Eichenbaum, and Evans (2005).

[2] See Ball and Romer (1990).

formance across an early and a late sample period. We break our sample in the early 1980s because numerous studies find that important changes in the conduct and transmission of monetary policy and in the behavior of inflation and output occurred during that period. For example, McConnell and Perez-Quiros (2000) identify 1984:Q1 as the beginning of a period of reduced variability in output growth, while Duffy and Engle-Warnick (2006) identify 1979:Q3 and 1980:Q3 as the most likely dates for a major shift in the conduct of monetary policy. Not coincidently, the Federal Reserve significantly changed its operating procedure in the fall of 1979, and the Monetary Control Act of 1980 began a phase-out of interest rate ceilings and other financial regulations. As for inflation, empirical studies find its persistence and variability began to decline in late 1981 or in early 1982 [Piger (2008)]. Based on our own Quandt-Andrews test results, applied to GDP inflation, we use 1981:Q3 as the dividing line between early and late samples in our estimations.[3] That date coincides with the beginning of a recession which many economists believe was deliberately induced to lower inflation. The summer of 1981 was also when President Reagan fired striking air-traffic controllers, signaling a new resistance to union wage demands.[4]

Maximum likelihood is utilized to estimate our DSGE models over each subsample. Three different DSGE models are considered: a sticky price and wage model with static indexation, a sticky price and wage model with dynamic indexation, and a sticky information model. After estimation, we use a Bayesian-motivated, pseudo-odds measure to judge which model fits the data best. Early-sample results strongly favor the sticky price and wage model with dynamic indexation over both the sticky information and the sticky prices and wages with static indexation models. In the late sample, however, sticky information and static indexation are competitive with one another, and dominate dynamic indexation. Thus, a shift in price- and wage-setting behavior appears occurred in the early 1980s in response to the pronounced changes in the economic environment at that time. The change is in the direction that one would expect given the reduced persistence and greater predictability of inflation in the late sample.

1.2 Relationship to the Existing Literature

Sticky information models are time consuming to estimate because they contain a large number of state variables. As a result, only a few studies–notably, Andre, Lopez-Salido, and Nelson (2005) and Laforte (2007)–compare the empirical performance of sticky price and sticky information frictions in an estimated DSGE model. Our analysis differs from these papers in two key respects. First, we estimate our models over both early and late sample periods rather than only a late sample pe-

[3] We also examined a 1979:Q3 breakpoint with similar results.

[4] The air-traffic controllers' strike began on August 3, 1981. The controllers were fired 48 hours later.

riod.[5] Splitting the sample allows us to explore the endogeneity of nominal rigidities. Second, our models include nominal wage rigidities in addition to price rigidities. Christiano, Eichenbaum, and Evans (2005) argue that including wage rigidities "is crucial for [a] model's performance." The findings from both papers, nonetheless, are generally consistent with our late-sample results. Specifically, Andre, Lopez-Salido, and Nelson (2005) argue that sticky information dominates sticky prices with dynamic indexation, while Laforte (2007) finds that sticky information performs about as well as sticky prices with static indexation, and that both models do better than sticky prices with dynamic indexation. One difference with our paper is that our sticky information and static indexation models are competitive with VAR models in the late sample, whereas Laforte (2007) finds that a VAR model fits the data best.

Other papers that have compared sticky price and sticky information frictions across multiple estimation periods include Ireland (2001), Kiley (2007), Korenok (2008), Coibion and Gorodnichenko (2009), Dupor, Kitamura, and Tsuruga (forthcoming), and Coibion (forthcoming). Dupor, Kitamura, and Tsuruga (forthcoming), like us, evaluate sticky price and sticky information frictions over early- and late-sample periods. Their models, however, are partial equilibrium, and they do not consider dynamic indexation.[6] A hybrid model, with both sticky prices and sticky information, consistently performs best according to these authors.

Like Dupor, Kitamura, and Tsuruga (forthcoming), Korenok (2008), Coibion and Gorodnichenko (2009), and Coibion (forthcoming) compare a sticky information model with a sticky price model with static indexation while ignoring dynamic indexation. Each presents full-sample and late-sample estimation results, rather than early-sample and late-sample results.[7] Only Coibion and Gorodnichenko (2009) use a general equilibrium framework. Late-sample results vary depending on the paper. Korenok (2008) and Coibion (forthcoming) determine that the static indexation model is superior to the sticky information model, whereas Coibion and Gorodnichenko (2009), like us, find that the two models perform similarly.

Kiley (2007) evaluates several different pricing rules, including sticky information and both static and dynamic indexation models, over a 1965-2002 sample and a 1983-2002 sample. His late-sample results differ substantially from our findings. In particular, Kiley (2007) claims that the dynamic indexation model fits the data slightly better than either the sticky information model or the static indexation model. One potential explanation for the different result is that we estimate a DSGE model, whereas Kiley (2007) estimates a model comprised of a structural-pricing equation and three reduced-form equations. Reduced-form models are less vulnerable to mis-

[5] Andre, Lopez-Salido, and Nelson (2005) and Laforte (2007) estimate their models over 1979:Q3-2003:Q3 and over 1983:Q1-2003:Q1, respectively.

[6] The authors detrend inflation which makes their sticky price component equivalent to our model with static indexation.

[7] Korenok (2008) and Coibion and Gorodnichenko (2009) start their late samples in 1983:Q1, whereas Coibion (forthcoming) starts his sample in 1984:Q1.

specification than DSGE models, but they are also estimated less efficiently.

Finally, Ireland (2001) estimates a DSGE model with sticky prices over both early and late sample periods (the sample breakpoint is 1979:Q2). Ireland (2007), like us, finds evidence of instability across samples. The instability, however, is in the household's discount factor and not in the pricing equation.

1.3 Outline

The remainder of the paper is structured as follows. Section 2 describes our empirical analysis of the persistence and predictability of inflation. Section 3 outlines the DSGE model, including the different specifications of price and wage rigidities. Section 4 discusses our estimation procedure. Section 5 presents the parameter estimates for each model and the pseudo-odds measure used to assess which model best fits the data. Section 6 examines the variance decompositions and impulse response functions for each model. Finally, Section 7 summarizes our main findings and offers suggestions for future research.

2 The Behavior of Inflation

This section examines the degree of persistence and predictability of inflation and whether the observed aggregate inflation process exhibits a break. Changes in the behavior of aggregate inflation and inflation expectations are important because they may reflect changes in how firms adjust their prices both when given an opportunity to reoptimize and between such opportunities. To determine the most likely date for a break in the inflation process, we use the Quandt-Andrews test. Our results suggest that a break occurred in the second or third quarter of 1981. Using that breakpoint, we find that inflation is more persistent and more variable in the early-sample period, and less persistent and more stable in the late-sample period.

2.1 Approximating the Inflation Process

The price-setting mechanism chosen by firms may be influenced by the behavior of aggregate inflation. In a sticky price model with static indexation, firms increase their prices at the steady-state inflation rate between reoptimizations. That arrangement is most likely to be attractive when inflation remains fairly constant and any deviations from that constant are not very persistent. Similarly, firms raise their prices automatically by last period's inflation rate between reoptimizations in a sticky price model with dynamic indexation. The dynamic indexation approach is presumably most appealing when the inflation process approximates a random walk. Our task now is to compare the empirical performance of these two price-setting specifications and determine whether their relative performance has shifted. We are not necessarily concerned with finding the *best* characterization of inflation's behavior.[8]

To determine whether the inflation process is better approximated by a transitory variation around a constant or by a random walk, we regress the h-period change in inflation on the constant steady-state inflation rate and the h-period lagged inflation rate:

$$\pi_t - \pi_{t-h} = \alpha_1(\overline{\pi} - \pi_{t-h}) + \varepsilon_t, \tag{1}$$

where $\overline{\pi}$ is the steady-state inflation rate and $0 \leq \alpha_1 \leq 1$. The inflation process in (1) is estimated, separately, for inflation lags ranging from one to four periods. The inflation process is more strongly mean reverting when α_1 approaches 1, whereas inflation is closer to a random walk when α_1 approximates 0. The timing of shifts in α_1 is determined using the Quandt-Andrews test.

Results from the Quandt-Andrews test are presented in Panel A of Table 1. That test shows a clear break in the inflation relationship at 1981:Q3 for lags of 3 and 4 quarters. The most likely breakpoint at the 2-quarter lag is 1981:Q2, but that test statistic is not quite significant at the 5% level. Finally, there is no evidence of an inflation break in the 1-quarter-lag specification.[9]

Panel B of Table 1 displays the estimation results for (1) over the pre-1981:Q3 and post-1981:Q2 subsamples, with standard errors for the estimated coefficients in parentheses. The adjusted R^2 statistics range from 5% to 6% in the early sample and from 19% to 55% in the late sample. Estimates of α_1 always differ significantly from both 0 and 1, but are consistently two to three times larger in the late sample than in the early sample. Those larger estimates for α_1 indicate that inflation is far less persistent in the late-sample period. That result suggests that the inflation environment may have become more favorable for static indexation, relative to dynamic indexation, in the late sample.

[8] Stock and Watson (2007) take an alternative approach by modeling inflation as the sum of a permanent and a transitory stochastic component. Although the standard deviation of transitory innovations remains fairly constant over the entire sample, the magnitude of the permanent innovations fluctuates greatly. Permanent innovations rise rapidly in the late 1960s and early 1970s, remain high in the early 1980s, and then gradually decline. Davig and Doh (2008) examine potential reasons why the time-series properties of inflation changed. Their results suggest that monetary policy was passive during the 1970s and early 1980s, technology shocks were highly persistent during the late 1970s and early 1980s, and for intervals during the late 1950s and mid 1970s, and that mark-up shocks became less persistent during portions of the late 1970s and early 1980s. Lansing (2009) offers a very different explanation. He shows how the belief that inflation follows a Stock-Watson (2007) process can be self reinforcing, and can generate what appears to be time variation in inflation variability and persistence.

[9] Prior to 1982, there is evidence of additional breaks in the inflation process during the late 1960s and early 1970s, but no evidence exists for any post-1981 breaks. Overall, the inflation process is unstable for much of the pre-1982 sample, but is stable in the post-1981 sample. Piger (2008) reports similar results.

2.2 Forecasting Changes in Inflation

In the sticky information framework, firms preset a price path between each reoptimization opportunity. That style of price setting will tend to be more advantageous than static indexation whenever inflation movements are large but predictable. The comparison of sticky information with dynamic indexation is more complex. Sticky information allows firms to adjust prices in response to a wide variety of information. However, the information set is updated infrequently. Dynamic indexation, in contrast, restricts that response to a single piece of information (lagged inflation), but that information is only 1-period old. Dynamic indexation will tend to be more appealing when lagged inflation captures most of the relevant information for forecasting current inflation.

Accordingly, we regress the 1-quarter change in inflation onto the h-quarter lagged median inflation forecast from the Survey of Professional Forecasters ($SPF_{t-h}(\pi_t)$) less the 1-quarter lagged inflation rate:

$$\pi_t - \pi_{t-1} = \alpha_1(SPF_{t-h}(\pi_t) - \pi_{t-1}) + \varepsilon_t, \tag{2}$$

for $h = 1$, 2, 3, and 4.[10] An estimate of α_1 close to 1 indicates that substantial information beyond lagged inflation is helpful in predicting current inflation. Such a result would tend to support sticky information. If, on the other hand, α_1 is estimated close to 0, then lagged inflation approximates current inflation well, which would be a more favorable environment for dynamic indexation.

The Quandt-Andrews test is utilized to determine if evidence exists of a shift in α_1. Panel A of Table 2 shows that the Quandt-Andrews test statistics are insignificant at all horizons, which means that there is no statistical evidence of a shift in α_1. Therefore, we have no *a priori* grounds for suspecting a shift away from an environment favorable to dynamic indexation and toward an environment favorable to sticky information, or *vice versa*.

Panel B of Table 2 displays the estimation results from the pre-1981:Q3 and post-1981:Q2 samples. Because the Quandt-Andrews test statistics are insignificant, it is not surprising that the estimates for α_1 are similar in the two samples. As h decreases, predicted inflation provides better information on current inflation, the standard errors for α_1 decline, and the adjusted R^2 statistic rises. With the exception of $h = 4$ in the early sample, the hypothesis that $\alpha_1 = 0$ is rejected. These results suggest that the SPF median inflation forecast has useful information beyond that of the 1-quarter lagged inflation rate. Finally, the 1-quarter lag of inflation has marginal predictive power beyond the SPF forecast even at the shortest horizons, suggesting that the SPF forecasts are inefficient.

Table 3 presents the summary statistics for the SPF median inflation forecasts at various horizons over both sample periods. These statistics reveal that expected

[10] The estimates for (2) are based on a shorter sample period because the Survey of Professional Forecasters' data on expected inflation begins in 1968:Q4.

inflation is lower and is much less variable in the late sample than in the early sample. The average expected inflation rate also is nearly constant across horizons in the late-sample period. Expected inflation averages a 3.0% annualized rate at a 1-quarter forecast horizon, which is similar to the 3.3% expected inflation rate at a 4-quarter horizon. In the early sample, in contrast, longer-term forecasts generally call for a lower inflation rate than near-term forecasts. Specifically, the average inflation forecast is a 6.3% annualized rate at the 1-quarter horizon, versus a 5.5% rate at a 4-quarter horizon. The lower variability and flatter profile of inflation forecasts after 1981 suggest that static indexation might have become more appealing relative to sticky information.

2.3 Summary and Observations

Inflation movements appear to have become less persistent sometime around the middle of 1981. Such a reduction in persistence might have encouraged firms to utilize static indexation instead of dynamic indexation between price reoptimizations. Inflation expectations also seem to have become more stable after 1981, which further supports the argument in favor of a shift toward static indexation.

Other researchers have also documented shifts in the behavior of inflation and inflation expectations. Evans and Wachtel (1993) estimate a Markov-switching model of the inflation process and find that inflation follows a random walk between the late 1960s and early 1980s. The innovations to the random walk have a large variance and this, combined with regime uncertainty, produces high inflation-forecast uncertainty. The combination of high inflation persistence and forecast uncertainty during the period should favor dynamic indexation. Cogley and Sargent (2005) analyze inflation dynamics using a VAR model estimated with time-varying coefficients and stochastic volatilities. They find that core inflation trends upward between the early 1960s and 1980, falls sharply in 1981, and remains low and reasonably stable thereafter. Inflation persistence follows a similar pattern. Therefore, both smaller disturbances to exogenous variables and a shift in the conduct of monetary policy contribute to the change in inflation's behavior in the 1980s. Finally, Piger (2008) considers Bayesian Model Averaging across a wide variety of specifications of the inflation process. He finds evidence of a sharp fall in inflation persistence and inflation uncertainty at the beginning of 1982.

In summary, some combination of changes in monetary policy and changes in exogenous shock processes significantly transformed the behavior of aggregate inflation sometime in the early 1980s. That shift potentially altered pricing incentives at the firm level. To investigate this possibility, we estimate our DSGE models over distinct early and late samples.

3 The Models

We use a conventional dynamic stochastic general equilibrium (DSGE) model in which households set wages in a monopolistically competitive labor market and firms set prices in a monopolistically competitive goods market. Nominal rigidities, however, slow the adjustment of wages and prices. This section outlines the three alternative types of nominal wage and price rigidities which we will empirically evaluate. In particular, we consider a sticky price and sticky wage model with static indexation, a sticky price and sticky wage model with dynamic indexation, and a sticky information model of price and wage setting. The models include exogenous processes representing an aggregate demand shock, a technology shock, and a monetary policy shock and are estimated with data on output, inflation, and the nominal interest rate.

3.1 Households

The household sector comprises a continuum of households, $h \in [0,1]$, which are monopolistically competitive suppliers of labor. Specifically, household h is an infinitely-lived agent who prefers to purchase consumption goods, c_t, and hold real money balances, M_t/P_t, but dislikes working, $n_{h,t}$. The preferences of household h are represented by the following expected utility function:

$$U = E_t \left[\sum_{j=0}^{\infty} \beta^j a_{t+j} \left(\ln(c_{t+j} - bc_{t+j-1}) + \theta_M \ln\left(\frac{M_{t+j}}{P_{t+j}}\right) - \theta_n \frac{n_{h,t+j}^{1+\zeta} - 1}{1+\zeta} \right) \right], \quad (3)$$

where E_t is the expectational operator at time t, β is the personal discount factor with a value between 0 and 1, b is the internal habit persistence in consumption parameter and is also between 0 and 1, θ_M and θ_n are the nonnegative parameters on real money balances and labor supply, respectively, and ζ is the inverse of the labor supply elasticity with respect to the real wage. The preference variable, a_t, represents an aggregate demand shock which evolves in the following manner:

$$\ln(a_t) = \rho_a \ln(a_{t-1}) + \varepsilon_{a,t},$$

where $-1 < \rho_a < 1$ and $\varepsilon_{a,t}$ is normally distributed with a standard deviation of σ_a.[11] Although household h has pricing power in the labor market, nominal wage frictions prevent it from either optimally setting a new wage every period or updating the information used to set that wage. Nominal wage frictions also cause the labor supply and the wage rate to differ among households. To maintain the tractability of the model, we assume that households participate in a state-contingent securities market guaranteeing each household the same income, so that all of the households make identical decisions on their remaining choice variables.[12]

[11] McCallum and Nelson (1999) argue that a_t resembles a shock to the IS curve in a traditional IS/LM model.

[12] Erceg, Henderson, and Levin (2000) and Christiano, Eichenbaum, and Evans (2005) use the same modeling technique.

Household h begins each period with its nominal money balances, M_{t-1}, carried over from last period and the principle plus interest on its current bond holdings, $R_{t-1}B_{t-1}$, where R_t is the gross nominal interest rate between periods t and $t+1$ and B_t is the nominal bond holdings. Labor earnings, $W_{h,t}n_{h,t}$, and capital rental income, $P_t q_t k_t$, are received by household h during period t, where $W_{h,t}$ is the nominal wage rate earned by household h, q_t is the real rental rate of capital, P_t is the price level, and k_t is the capital stock. Additionally, household h receives dividends, D_t, from its ownership interest in the firms, a transfer, T_t, from the monetary authority, and a payment, $A_{h,t}$, from its participation in the state-contingent securities market. Those assets are utilized to purchase consumption and investment goods and to finance end-of-period money and bond holdings. The flow of funds for household h is described by the following budget constraint:

$$P_t(c_t + i_t) + M_t + B_t = M_{t-1} + R_{t-1}B_{t-1} + W_{h,t}n_{h,t} + P_t q_t k_t + D_t + T_t + A_{h,t}. \quad (4)$$

Investment purchases, i_t, in (4) are converted into capital according to the equation:

$$k_{t+1} - k_t = \varphi(i_t/k_t)k_t - \delta k_t, \quad (5)$$

where δ is the depreciation rate. The functional form $\varphi(\cdot)$ in (5) represents the capital adjustment costs associated with the conversion of investment to capital. Because the resources lost in the conversion, $i_t - \varphi(i_t/k_t)k_t$, are assumed to be increasing and convex, the functional form $\varphi(\cdot)$ is increasing and concave with respect to the steady-state, investment-to-capital ratio, i/k (i.e., $\varphi'(\cdot) > 0$, $\varphi''(\cdot) < 0$).

Household h is a monopolistically competitive supplier of differentiated labor services, $n_{h,t}$, to the firms. The labor services provided by all of the households are combined according to Dixit and Stiglitz's (1977) aggregation technique to calculate total aggregate labor hours, n_t:

$$n_t = \left[\int_0^1 {n_{h,t}}^{(\epsilon_W - 1)/\epsilon_W} dh\right]^{\epsilon_W/(\epsilon_W - 1)},$$

where $-\epsilon_W$ is the wage elasticity of demand for $n_{h,t}$. The demand by firms for household h's labor services is a decreasing function of household h's relative wage:

$$n_{h,t} = \left(\frac{W_{h,t}}{W_t}\right)^{-\epsilon_W} n_t, \quad (6)$$

where W_t is interpreted as the aggregate nominal wage:

$$W_t = \left[\int_0^1 {W_{h,t}}^{1-\epsilon_W} dh\right]^{1/(1-\epsilon_W)}.$$

3.1.1 Nominal Wage Frictions

We examine the effects of three popular models of wage setting: sticky wages with static indexation, sticky wages with dynamic indexation, and sticky information wages. In both of the sticky wage specifications, household h is provided periodically with an opportunity to negotiate a new nominal wage contract. The difference between static and dynamic indexation is in how household h's nominal wage adjusts in the absence of an opportunity to renegotiate. In the static indexation specification, households, who are unable to renegotiate, raise their nominal wage by the steady-state inflation rate, whereas in the dynamic indexation specification, households increase their nominal wage by last period's inflation rate.[13] Finally, the sticky information friction enables household h to select a new nominal wage every period, but the information used to set that wage updates infrequently.

Sticky Wages with Static Indexation: This friction, as in Erceg, Henderson, and Levin (2000), assumes that households set their wage according to a Calvo (1983) model of random adjustment. Specifically, a household has a probability of η_W that it will receive an opportunity to optimally reset its nominal wage. If that opportunity is absent, then that household's wage automatically rises by the steady-state inflation rate, π. A household which has an opportunity to optimally reset its nominal wage selects a nominal wage, W_t^*, that maximizes the present value of its current and expected future utility, (3), subject to its budget constraint, (4), the firms' demand for its labor, (6), and the probability, $(1-\eta_W)^j$, that another wage-resetting opportunity will not occur in the subsequent j periods. The solution to household h's wage-setting problem yields the following first-order condition:

$$E_t\left[\sum_{j=0}^{\infty}\beta^j(1-\eta_w)^j\left(\frac{\pi^j W_{0,t}}{P_{t+j}}-\frac{\varepsilon_w}{\varepsilon_w-1}\left(\frac{-U_{n(h),t+j}}{U_{c,t+j}}\right)\right)n_{h,t+j}\right]=0, \tag{7}$$

where $U_{c,t}$ is the marginal utility of consumption and $U_{n(h),t}$ is the marginal utility of labor for household h. On the right-hand side of (7), the value $-U_{n(h),t}/U_{c,t}$ is interpreted as the marginal rate of substitution of consumption for labor and $\varepsilon_w/(\varepsilon_w-1)$ is the steady state mark-up of the real wage over the marginal rate of substitution. The absence of an h in the marginal utility of consumption reflects the fact that the state-contingent securities market equalizes consumption (but not labor) among households.

Sticky Wages with Dynamic Indexation: The sticky wage specification with dynamic indexation, like that of Christiano, Eichenbaum, and Evans (2005), is similar to the model with static indexation, except that the nominal wage for nonadjusting households automatically rises by last period's inflation rate. Specifically, the probability that a household can negotiate a new nominal wage is η_w, whereas the

[13] Eichenbaum and Fisher (2007) introduce the terminology "static" and "dynamic" indexation to describe the automatic adjustment of wages or prices which cannot be reoptimized in a given period.

probability that its wage increases by last period's inflation rate, π_{t-1}, is $(1-\eta_w)$. The first-order condition for the wage-adjusting household with dynamic indexation is as follows:

$$E_t\left[\sum_{j=0}^{\infty}\beta^j(1-\eta_w)^j\left(\frac{\Pi_{t+j}W_{0,t}}{P_{t+j}}-\frac{\varepsilon_w}{\varepsilon_w-1}\left(\frac{-U_{n(h),t+j}}{U_{c,t+j}}\right)\right)n_{h,t+j}\right]=0$$

such that $\Pi_t = 1$ and $\Pi_{t+j} = \pi_{t+j-1}\times\Pi_{t+j-1}$ for $j \geq 1$.

Sticky Information Wages: The final nominal wage friction to be examined is sticky information as in Koenig (1996, 1999, 2000). In that specification, household h can set a new nominal wage every period, but the information used to set that wage updates infrequently. Formally, household h acquires new information with a probability of η_w, whereas it must utilize the information that it obtained j periods ago with a probability of $(1-\eta_w)$. The objective of household h then is to maximize its current expected utility, (3), subject to its budget constraint, (4), and the firms' demand for its labor, (6), given that its expectations were last updated j periods ago. Because wages adjust every period but information is sticky, household h's first-order condition indicates that the optimal nominal wage, $W_{h,t}$, is equal to the expected value from j periods ago of the nominal value of the marginal rate of substitution multiplied by the steady-state wage mark-up:

$$W_{h,t}-\frac{\varepsilon_w}{\varepsilon_w-1}E_{t-j}\left[P_t\left(\frac{-U_{n(h),t}}{U_{c,t}}\right)\right]=0.$$

3.2 Firms

Firms are entities owned by the households which produce differentiated goods in a monopolistically competitive market, but encounter price frictions that interfere with optimal price adjustment. Firm f hires labor, $n_{f,t}$, at a real wage rate of w_t and rents capital, $k_{f,t}$, at a real rental rate of q_t. Those labor and capital inputs and the level of technology, Z_t, are utilized by firm f to produce its output, $y_{f,t}$, according to a Cobb-Douglas production function:

$$y_{f,t} = Z_t(k_{f,t})^{\alpha}(n_{f,t})^{1-\alpha}, \tag{8}$$

where $0 \leq \alpha \leq 1$. The technology variable, Z_t, evolves such that

$$\ln(Z_t) = \rho_Z\ln(Z_{t-1}) + (1-\rho_Z)\ln(Z) + \varepsilon_{Z,t},$$

where Z is the steady state value of Z_t, $-1 < \rho_Z < 1$, and $\varepsilon_{Z,t}$ is normally distributed with a standard deviation of σ_Z. As a profit-maximizing agent, firm f minimizes its production costs subject to (8). The resulting labor and capital factor demands equal:

$$\psi_t(1-\alpha)Z_t[k_{f,t}/n_{f,t}]^{\alpha} = w_t, \tag{9}$$

$$\psi_t \alpha Z_t [n_{f,t}/k_{f,t}]^{1-\alpha} = q_t, \tag{10}$$

where ψ_t is the Lagrange multiplier from the cost minimization problem and is interpreted as the real marginal cost of producing an additional unit of output. The real marginal cost then can be determined by combining (9) and (10):

$$\psi_t = \frac{(q_t)^{\alpha}(w_t)^{1-\alpha}}{Z_t(\alpha)^{\alpha}(1-\alpha)^{1-\alpha}}.$$

Because the real wage, real rental rate of capital, and the level of technology are economy-wide variables, the real marginal cost is the same across all firms.

Aggregate output, y_t, is a Dixit and Stiglitz (1977) continuum of differentiated goods, $y_{f,t}$, where $f \in [0,1]$ such that

$$y_t = \left[\int_0^1 y_{f,t}^{(\varepsilon_p - 1)/\varepsilon_p} df\right]^{\varepsilon_p/(\varepsilon_p - 1)},$$

where $-\varepsilon_p$ is the price elasticity of demand for $y_{f,t}$. Cost minimization by the households generates the following demand equation for firm f's good:

$$y_{f,t} = \left(\frac{P_{f,t}}{P_t}\right)^{-\varepsilon_p} y_t, \tag{11}$$

where $P_{f,t}$ is the price for $y_{f,t}$ and P_t is a nonlinear aggregate price index:

$$P_t = \left[\int_0^1 P_{f,t}^{1-\varepsilon_p} df\right]^{1/(1-\varepsilon_p)}.$$

3.2.1 Price Frictions

In much the same way as we examined the households' wage-setting behavior, we investigate three popular types of price frictions: sticky prices with static indexation, sticky prices with dynamic indexation, and sticky information prices. Both sticky price specifications assume that a random fraction of firms can adjust their prices in any given period. The remaining firms must increase their prices by the steady-state inflation rate in the static indexation specification and by last period's inflation rate in the dynamic indexation specification. In the sticky information case, prices are flexible, but firms intermittently update the information used to set those prices.

Sticky Prices with Static Indexation: As in Erceg, Henderson, and Levin (2000), price-setting behavior follows a Calvo (1983) model of random adjustment. That is, the probability that a firm can optimally adjust its price is η_P; otherwise, its price increases by the steady-state inflation rate, π. Those firms which are able to optimally reset select a price, $P_{0,t}$, which maximizes its present value of current and expected future profits subject to its factor demand equations, (9) and (10), households' demand for its goods, (11), and the probability, $(1-\eta_P)^j$, that another price-adjustment opportunity will not occur in the subsequent j periods. Firm f's efficiency condition when it selects a new price is

$$E_t\left[\sum_{j=0}^{\infty}\beta^j(1-\eta_P)^j\lambda_{t+j}\left(\frac{\pi^j P_{0,t}}{P_{t+j}}-\frac{\varepsilon_P}{\varepsilon_P-1}\psi_{t+j}\right)y_{f,t+j}\right]=0,$$

where λ_t represents the households' marginal utility of an additional dollar of profits (i.e., $\lambda_t = U_{c,t}$).

Sticky Prices with Dynamic Indexation: Christiano, Eichenbaum, and Evans' (2005) technique of dynamic indexation in a Calvo (1983) pricing model requires nonprice-adjusting firms to raise their prices by last period's inflation rate. Formally, a firm has the probability η_P that it will be able to select a new price and the probability $(1-\eta_P)$ that its price rises by last period's inflation rate, π_{t-1}. The first-order condition for a price-adjusting firm in a sticky price specification with dynamic indexation is

$$E_t\left[\sum_{j=0}^{\infty}\beta^j(1-\eta_P)^j\lambda_{t+j}\left(\frac{\Pi_{t+j} P_{0,t}}{P_{t+j}}-\frac{\varepsilon_P}{\varepsilon_P-1}\psi_{t+j}\right)y_{f,t+j}\right]=0$$

such that $\Pi_t = 1$ and $\Pi_{t+j} = \pi_{t+j-1} \times \Pi_{t+j-1}$ for $j \geq 1$.

Sticky Information Prices: Sticky information in price setting, as in Koenig (1996, 1999), Mankiw and Reis (2002, 2007), and Keen (2007), assumes that all prices can adjust every period, but that the information used by firms to set those prices adjusts infrequently. In particular, firm f's information set either updates with a probability of η_P or remains unchanged from j periods ago with a probability of $(1-\eta_P)$. Using its expectations formed j periods ago, firm f sets a price which maximizes its expected profits subject to its factor demand equations, (9) and (10), and households' demand for its goods, (11). Firm f's first-order condition indicates that it selects a price, $P_{f,t}$, based on expectations formed j periods ago of its nominal marginal cost in period t multiplied by the steady-state price mark-up:

$$P_{f,t}-\frac{\varepsilon_P}{\varepsilon_P-1}E_{t-j}\left[P_t\psi_t\right]=0.$$

3.3 Monetary Authority

The monetary authority utilizes a generalized Taylor (1993) nominal interest rate rule which incorporates both a Clarida, Gali, and Gertler (2000) style smoothing of the nominal interest rate and an endogenous policy response to the output growth rate, $g_t^y = y_t/y_{t-1}$, as in Ireland (2004, 2007) and Coibion and Gorodnichenko (2009). Specifically, the nominal interest rate responds to deviations of the lagged nominal interest rate, the current inflation rate, and the current output growth rate from their respective steady states:

$$\ln(R_t/R)=\phi_R\ln(R_{t-1}/R)+\phi_\pi\ln(\pi_t/\pi)+\phi_y\ln(g_t^y/g^y)+\upsilon_{R,t},$$

where the variables without time subscripts are steady-state values, $0 \leq \phi_R \leq 1$, $\phi_\pi > 0$, and $\phi_y > 0$. The disturbance term, $\upsilon_{R,t}$, is a transitory monetary policy shock which follows an autoregressive process:

$$\upsilon_{R,t} = \rho_R \upsilon_{R,t-1} + \varepsilon_{R,t},$$

where $-1 < \rho_R < 1$ and $\varepsilon_{R,t}$ is normally distributed with a standard deviation of σ_R.

4 Equilibrium and Estimation Procedure

The different styles of nominal wage and price rigidities are incorporated into the following three DSGE models: a sticky price and sticky wage model with static indexation, a sticky price and sticky wage model with dynamic indexation, and a sticky information model of price and wage setting. Each model's respective equations from the households, firms, and monetary authority sectors form a set of equations describing the systematic equilibrium of that model. Because each model includes a positive steady-state rate of inflation, the nominal variables, P_t^*, $P_{f,t}$, W_t, W_t^*, $W_{h,t}$, $A_{h,t}$, T_t, M_t, B_t, and D_t are divided by P_t to induce stationarity and thus, each model is able to converge to its nonstochastic steady-state equilibrium.[14] The system of equations for each model is then log-linearized around its nonstochastic steady state. The rational expectations solution can be obtained for both the sticky price and sticky wage models by utilizing traditional solution methods, such as Blanchard and Kahn (1980), King and Watson (1998, 2002), or Sims (2002). As for the sticky information model, the presence of lagged expectations greatly expands the size of the model in the traditional solutions framework. That problem often forces researchers to limit the number of lagged expectations equations and as a result, potentially changes the dynamics of the model. We circumvent that problem by using Wang and Wen's (2006) method of undetermined coefficients to find the sticky information model's rational expectations solution. The model size in Wang and Wen's (2006) solution framework, however, expands proportionally with the number of exogenous disturbances, which exponentially increases the time it takes to generate a solution. Given that constraint, we limit the number of exogenous disturbances in our models to three.

The rational expectations solution for each model is transformed into the following state space system:

$$\mathbf{s}_t = \mathbf{M}\mathbf{s}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{12}$$

$$\mathbf{Y}_t = \boldsymbol{\Pi}\mathbf{s}_t, \tag{13}$$

where $\mathbf{Y}_t$ is a vector of observed variables, $\mathbf{s}_t$ is a vector of observed and unobserved variables, $\boldsymbol{\varepsilon}_t$ is a vector of innovations, and $\mathbf{M}$ and $\boldsymbol{\Pi}$ are matrices containing the

[14] In spite of the differences in the three forms of nominal rigidities, all of the models converge to the same steady state.

underlying parameters of the model. Each variable included in the vectors $\mathbf{s}_t$ and $\mathbf{Y}_t$ is specified as that variable's logarithmic deviation from its steady state. Output, the inflation rate, and the nominal interest rate are the observed variables in $\mathbf{Y}_t$, while $\boldsymbol{\varepsilon}_t$ comprises the three exogenous shocks, $\varepsilon_{a,t}$, $\varepsilon_{Z,t}$, and $\varepsilon_{R,t}$. The number of observed variables in $\mathbf{Y}_t$ is set equal to the number of disturbances in $\boldsymbol{\varepsilon}_t$ to eliminate the need for any measurement error in (13).[15] Finally, our specification of the exogenous shocks results in $\boldsymbol{\varepsilon}_t$ being normally distributed with a diagonal covariance matrix $E[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'] = \boldsymbol{\Omega}$.

The state-space representation of the model solution, (12) and (13), is convenient for calculating the likelihood function via the Kalman filter. The Kalman filter generates the optimal linear projections of the observed variables, $\mathbf{Y}_{t|t-1}$, from (13) based on $\ddot{\mathbf{Y}}_{t-1} \equiv (\mathbf{Y}_{t-1}, ..., \mathbf{Y}_1)$. The assumption that $\boldsymbol{\varepsilon}_t$ and the initial state $\mathbf{s}_1$ are Gaussian means that the distribution of $\mathbf{Y}_t$ conditional on $\ddot{\mathbf{Y}}_{t-1}$ can be specified as follows:

$$\mathbf{Y}_t|\ddot{\mathbf{Y}}_{t-1} \sim N(\boldsymbol{\Pi}\mathbf{s}_{t|t-1}, \boldsymbol{\Pi}'\mathbf{P}_{t|t-1}\boldsymbol{\Pi}),$$

where $\mathbf{P}_{t|t-1} = E[(\mathbf{s}_t - \mathbf{s}_{t|t-1})(\mathbf{s}_t - \mathbf{s}_{t|t-1})']$. That result enables us to generate the sample log-likelihood function conditional on $\mathbf{s}_1$:

$$L(\Theta) = \sum_{t=2}^{T} \log f_{\mathbf{Y}_t|\ddot{\mathbf{Y}}_{t-1}}(\mathbf{Y}_t|\ddot{\mathbf{Y}}_{t-1}, \Theta), \tag{14}$$

where Θ is a vector of the parameters contained in $\boldsymbol{\Pi}$, $\mathbf{M}$, and $\boldsymbol{\Omega}$.[16] Those parameters then are estimated by numerically maximizing (14) with respect to Θ.

Our model is estimated using U.S. data on output, inflation, and the nominal interest rate from 1954:Q3-2006:Q4. Output is expressed in per capita terms by dividing the chain-weight measure of gross domestic product by the civilian, noninstitutional population, age 16 and over. To eliminate the long-run growth component, the output series is linearly detrended by its average quarterly growth rate over the estimated sample period.[17] The inflation rate is calculated as the rate of change in the gross domestic product implicit price deflator. Finally, the effective federal funds rate is our measure of the nominal interest rate.

[15] Any model with more observed variables than innovations requires the addition of error terms to (13) to prevent the covariance matrix of the data from being singular.

[16] See Hamilton (1994, Ch. 13) for a detailed description of the Kalman filter.

[17] The average quarterly growth rate of output is 0.0046146 for the models estimated over the 1954:Q3-1981:Q2 sample period and is 0.0045898 for the models estimated over the 1981:Q3-2006:Q4 sample period.

5 Estimation Results and Performance Comparisons

5.1 Estimating the Models

The absence of information on investment, capital, employment, and wages means that some parameters remain either unidentified or weakly identified. Those parameters then need to be set prior to estimating the model. Specifically, the lack of investment and capital data makes it difficult to estimate capital's share of output, α, the depreciation rate, δ, and the size of the capital adjustment costs. Capital's share of output is assumed to be 0.33, whereas the depreciation rate is set to a quarterly rate of 2.5%. Our rational expectations solution method does not require an exact functional form for the capital adjustment costs, $\varphi(i_t/k_t)$. Instead, we only need to specify parameter values for φ, φ', and φ''. We set φ equal to the steady-state investment-to-capital ratio, i/k, and φ' equal to 1, so that the average and marginal capital adjustment costs around the steady state are zero. To be consistent with Chirinko's (1993) empirical estimates, the remaining capital adjustment costs parameter φ'' is parameterized so that the elasticity of the investment-to-capital ratio with respect to Tobin's q, $[-(i/k)\varphi''/\varphi']^{-1}$, equals 1.

In a similar way, the absence of labor market data compels us to calibrate certain parameters in the utility function. The elasticity of the labor supply with respect to the real wage, $1/\zeta$, is parameterized to Christiano and Eichenbaum's (1992) estimate of 5, whereas the preference parameter θ_n is set so that steady-state labor equals 0.2. It is unnecessary, however, to specify or estimate a value for the preference parameter θ_M, because it only enters the money demand equation, which is easily dropped from our model. We initially assume that households do not exhibit habit persistence in consumption ($b = 0$), but later in the paper we discuss how including habit persistence impacts our results. Finally, the lack of wage data makes identifying the price mark-up, the wage mark-up, and the probability of nominal wage reoptimization difficult. We set both the price elasticity of demand, ϵ_P, and the wage elasticity of labor demand, ϵ_W, to 6, which is consistent with Erceg, Henderson, and Levin's (2000) assumption that price and wage mark-ups average 20%. The probability that household h can optimally adjust its nominal wage, η_w, is set to 0.25, which implies that household h, on average, optimally resets its nominal wage once a year.

All three of our models are estimated via maximum likelihood over an early-sample period (1954:Q3-1981:Q2) and a late-sample period (1981:Q3-2006:Q4). As mentioned earlier, it is not uncommon for models to be estimated either over a split sample or over a sample that begins in the late 1970s or early 1980s. Late sample start dates have ranged from 1979:Q3 (when the Fed started manipulating non-borrowed reserves, with an eye toward achieving money-growth targets) to 1983:Q1 (when the Fed began adjusting borrowed reserves in response to changes in inflation and slack) to 1984:Q1 (the start of the "Great Moderation" in real GDP growth).[18]

Within each sample period, we follow Ireland's (2004, 2007) practice of fixing the parameter values of Z, π, and β to insure that the steady-state values of output, the inflation rate, and the nominal interest rate match their respective average values in the data. Ireland (2004) argues that such an approach "guards against the possibility that otherwise, the estimated model will attempt to account for systematic deviations of the observed variables from their steady-state levels by overstating the persistence of the exogenous shocks." As a result, we set $z = 1041.72$, $\pi = 1.0108$, and $\beta = 0.9972$ in the early sample and $z = 1494.68$, $\pi = 1.0069$, and $\beta = 0.9921$ in the late sample. The remaining ten parameters: η_p, ϕ_R, ϕ_π, ϕ_y, ρ_Z, ρ_a, ρ_R, σ_Z, σ_a, and σ_R are estimated for our models over both sample periods.[19]

Tables 4-6 display the maximum-likelihood parameter estimates and standard errors for our three structural models.[20] The estimated coefficients of the sticky price and wage model with static indexation, as shown in Table 4, are broadly similar across sample periods, with a few exceptions. The variances of the technology, aggregate demand, and monetary policy shocks are estimated to be substantially higher in the early sample than in the late sample, which is consistent with Cogley and Sargent (2005). Preference shocks are slightly more persistent in the early sample, whereas technology shocks are somewhat less persistent. Prices are also estimated to be reoptimized, on average, approximately once every 10 quarters in the early sample, compared to roughly once every 4 quarters in the late sample.

Parameter estimates for the sticky price and wage model with dynamic indexation are presented in Table 5. As in the static indexation model, the variances of the technology, aggregate demand, and monetary policy shocks are higher and the preference shock exhibits more persistence during the early period. The estimated frequency with which prices are reoptimized remains essentially the same in both sample periods. The parameter estimates also suggest that the dynamic indexation model displays extreme interest-rate smoothing ($\phi_R = 1$) in the early sample, which is consistent with Ireland's (2007) monetary policy rule. One peculiar result in the dynamic indexation model is that technology shocks are essentially white noise, whereas in the static indexation model they are highly persistent.

Table 6 presents the parameter estimates for the sticky information model. The estimated frequency of price reoptimization is roughly once every 7 quarters, on average, in both sample periods. Monetary policy seems to be more activist in the early sample. In fact, the estimated coefficients on inflation and output growth are nearly equal, which implies that the Fed was responding to the growth rate of nomi-

[18] For example, Ireland (2001, 2003) begins his estimation in 1979:Q3, Del Negro et al. (2007) and Kiley (2007) in 1983:Q1, and Coibion (forthcoming) in 1984:Q1.

[19] Using similar data, Ireland (2004, 2007) also concentrates primarily on estimating the parameters associated with the policy rule and the exogenous disturbances in his models.

[20] The standard errors are calculated by inverting negative one multiplied by the log-likelihood function's matrix of second derivatives, and then taking the square root of the diagonal elements of that inverted matrix.

nal GDP. Aggregate demand shocks are slightly more persistent and the technology shocks somewhat less persistent in the early sample than in the late sample. Finally, the variances of our three exogenous shocks are all larger in the early period, which is consistent with both the static and dynamic indexation models.

5.2 Performance Comparison

We utilize the Bayesian information criterion (BIC) to compare the fit of our three estimated models to each other and to VAR models with lags of between 1 and 4 quarters.[21] The BIC for model i is calculated by penalizing its log-likelihood value, $L(i)$, by the number of estimated parameters, $N_P(i)$, and the sample size of the data, T, such that

$$BIC(i) = L(i) - \frac{N_P(i)}{2} \ln(T).$$

The BIC statistic then is used to calculate a Bayesian-style, pseudo-odds measure which generates a data-determined probability of model i:

$$\rho(i) = \frac{\exp(BIC(i))}{\sum_{j=1}^{z} \exp(BIC(j))},$$

where z is the number of models examined. As the value of $\rho(i)$ rises, the likelihood that the data is generated by model i rather than one of the alternative models increases.

Table 7 displays the BIC and pseudo-odds measure for the three structural models and the four VAR models.[22] Panels A and B present results for the early-sample period and the late-sample period, respectively. The first pseudo-odds calculation compares the static indexation and sticky information models, whereas the second comparison also includes the VAR models. All three structural models are compared in the third calculation, while the entire set of models are simultaneously compared in the fourth computation.

The results from our pseudo-odds measure differ greatly across our two sample periods. In the early sample, the sticky information model clearly fits the data better than the static indexation model and all of the VAR models. When the dynamic indexation model is included, however, virtually all of the pseudo-odds weight shifts to that model. In the late sample, the pseudo-odds weights for the static indexation and the sticky information models are roughly 3/5 and 2/5, respectively. That result suggests that the data slightly prefer the static indexation model in the late sample. When the VAR models are included, the static indexation model tracks the data

[21] Brock, Durlauf, and West (2003) and Kiley (2007) also utilize the BIC for model comparison in a non-Bayesian framework.

[22] The VAR model used is $X_t = A(L)X_{t-1} + e_t$, where $X_t = [y_t, \pi_t, R_t]^T$.

slightly better than the best-fitting VAR model, whereas the sticky information model performs slightly worse. Those results do not change when the dynamic indexation model is included in the analysis.

Our findings from the pseudo-odds measure are broadly consistent with the results reported in Tables 1 and 3. That is, aggregate inflation is much less persistent after 1981:Q2, which suggests that the inflation environment in our late sample might be more favorable to static indexation, relative to dynamic indexation. We also find that the SPF inflation expectations are more stable in the late sample than in the early sample. That result implies that static indexation might be relatively more appealing than sticky information in the late-sample period.

5.3 Robustness Check

This section briefly describes the robustness of the results reported in Table 7 to our wage-setting and habit-persistence assumptions. Specifically, we consider the impact of both flexible wages ($\eta_w = 1$) and internal habit persistence in consumption ($b = 0.25$ and $b = 0.95$) on our three structural models.[23] Without presenting all of the details, we note that relaxing our wage-setting and habit-persistence assumptions does not change our main results. That is, the dynamic indexation model fits the data best in the early sample, whereas the static indexation models fits best in the late sample. Our structural models, in most cases, perform slightly better with nominal wage rigidities, as opposed to flexible wages, but that result is usually statistically insignificant. This finding is consistent with our conjecture that η_w is weakly identified given that our observed variables are output, inflation, and the nominal interest rate. As for the degree of habit persistence, we find that the data prefer specifications with little or no habit persistence ($b = 0.25$ or $b = 0$). The lack of data on consumption, however, makes it difficult to precisely identify the degree of habit persistence.

6 Empirical Implications

6.1 Variance Decompositions

Tables 8, 9, and 10 show the forecast-error variance decompositions for output, inflation, and the nominal interest rate for each of our three estimated structural models over each sample period. The decomposition is conducted at horizons of 1, 4, 8, 12, 20, and 40 quarters, and in the limit as the forecast horizon approaches infinity. Note that the columns may not sum to 100 due to rounding errors.

The results from the variance decompositions are quite similar across the models. Monetary policy shocks have their largest impact on output in the short and medium runs, whereas technology and aggregate demand shocks have their largest impact on

[23] Ireland (2007) estimates the habit persistence parameter close to the lower value, whereas Andre, Lopez-Salido, and Nelson (2005) and Coibion and Gorodnichenko (2009) assume the higher value.

output at medium and long horizons. Generally, technology shocks are more important at business-cycle frequencies in the late sample than in the early sample, whereas monetary policy shocks are more important at those frequencies in the early sample than in the late sample. These results suggest that improved control of monetary policy contributed relatively more to the "Great Moderation" than did the reduction in the variance of technology shocks.

Aggregate demand shocks have a much different effect on output variability in the early sample than in the late sample. First, they account for a much smaller fraction of output variation, on average, in the late sample than in the early sample. Second, they tend to have their greatest impact at shorter horizons in the late sample than they do in the early sample.

Technology and aggregate demand shocks–not monetary policy shocks–are responsible for most of the variation in inflation and the nominal interest rate. This result holds across models, across sample periods, and across time horizons. For inflation, technology shocks are generally the biggest single source of variation. At medium and long horizons, though, aggregate demand shocks are often important, too. Finally, variations in the nominal interest rate are dominated by the aggregate demand shock at all horizons. Monetary policy shocks generally have little impact beyond the first few quarters.

6.2 Impulse Response Functions

Figures 1 and 2 show how output, inflation, and the nominal interest rate respond to monetary policy, technology, and aggregate demand shocks in our models. Figure 1 shows impulse response functions based on early-sample model estimates, while Figure 2 shows impulse responses based on late-sample estimates. The output and inflation charts show percent deviations from steady-state values. The interest-rate charts show arithmetic deviations from steady-state values, measured in basis points.

To begin, a positive technology shock produces an immediate decline in inflation and a positive, hump-shaped output response in all three models and in both sample periods. Since inflation falls but the real interest rate rises, the response of the nominal interest rate is ambiguous. In the early-sample period, the lower inflation rate usually dominates so that the nominal interest rate falls. The higher real interest rate, however, dominates in the late-sample period, which pushes up the nominal interest rate.

The response to an aggregate demand shock is similar across sample periods. Specifically, a positive aggregate demand shock increases current consumption at the expense of savings. That decline in savings raises both the nominal and real interest rates. The increased consumption demand initially pushes up output. Output eventually declines, however, because the resources diverted away from investment lower the capital stock, reducing the economy's productive capacity. The increased demand for goods also puts upward pressure on the inflation rate. Inflation follows a hump-shaped path in the dynamic indexation and sticky information models, but peaks on impact in the static indexation model.

Our models' predicted responses to a stimulative monetary policy shock exhibit several difficulties that are common in the DSGE literature. For example, all of the models fail to produce the hump-shaped output response observed in the data, and only the dynamic indexation model can generate an inflation response that peaks several periods after the shock.[24] These difficulties can be mitigated by introducing a richer set of real rigidities and learning into the models.[25] As for the nominal interest rate, it falls on impact, but its response in subsequent periods varies from model to model. With static indexation, output declines rapidly after its initial upward jump so that the monetary authority keeps the nominal interest rate low. Output remains elevated for longer in the dynamic indexation model, which puts upward pressure on inflation. The monetary authority reacts to the high and rising inflation by promptly raising the nominal interest rate. In the sticky information model, the nominal interest rate response depends on the sample period. The increase in inflation is large enough in the early sample period to push up the nominal interest rate with a one-period lag. That jump in inflation, however, is more modest in the late sample period so that the nominal interest rate declines.

7 Summary and Suggestions for Future Research

None of the models with nominal frictions that we examine–sticky prices and wages with static indexation, sticky prices and wages with dynamic indexation, or sticky-information prices and wages–performs consistently well over the entire post-World-War-II period. During an early sample, when aggregate inflation was both persistent and highly variable, the dynamic indexation model performs substantially better than the alternatives. In a late sample, the static indexation model and the sticky information model perform about equally well, and both fit the data better than the dynamic indexation model. Our results highlight the possibility that some popular models of price and wage adjustment are not "structural," because they do not endogenously respond to economic and policy changes. Macroeconomic analyses based on such models then ought to be considered as approximations which are valid only in relatively stable economic and policy environments.

Future research might proceed in two directions. One approach is to examine how a firm's preferred price-setting behavior varies in response to changes in the economic environment and the conduct of policy, while assuming that other firms also are optimally setting their prices. That is, carefully model the endogeneity of nominal frictions so that we can examine the circumstances under which one pricing

[24]See Altig et al. (2005) for documentation of these patterns.

[25]Christiano, Eichenbaum, and Evans (2005) develop a model with a rich set of real rigidities which can generate a hump-shaped output response, whereas Keen (forthcoming) demonstrates that incorporating learning into the model assists in producing a hump-shaped inflation response.

specification is likely to be preferred to the alternatives. In this vein, Cogley and Sbordone (2008) show that if the permanent component of inflation is identifiable, then price reoptimizing firms will systematically put greater weight on future economic conditions as trend inflation rises. Consequently, the coefficients in the New Keynesian Phillips curve vary endogenously with trend inflation.[26] Once Cogley and Sbordone (2008) take into account these shifting weights, they find no evidence of dynamic indexation in the data: Firms appear to hold their prices constant between reoptimizations. Cogley and Sbordone (2008) do not examine the subsample stability of their results.

The second avenue for future research is to develop a model of nominal frictions that is flexible enough to perform well over a wide range of circumstances. For example, Ireland (2007) estimates a DSGE model in which firms can index to a weighted average of lagged inflation and the monetary authority's time-varying target inflation rate. His empirical results indicate that firms completely index to the inflation rate target and place zero weight on lagged inflation.[27] Thus, firms may be even more sophisticated in their pricing than is allowed for by the static indexation, dynamic indexation, and sticky information models.

[26] See, also, Coibion and Gorodnichenko (2008), who examine the interaction between trend inflation, the degree to which price-reoptimization is forward looking, and the possible indeterminacy of monetary policy.

[27] Along the lines of Ireland (2007), Davig and Doh (2008) specify a price rule which enables an endogenous response to shifts in monetary policy. Davig and Doh (2008) assume that prices are indexed to trend inflation between reoptimizations, and that monetary policy switches between dovish and hawkish regimes. Firms then have to account for potential regime changes when optimizing their prices.

References

[1] Altig, David, Lawrence J. Christiano, Martin Eichenbaum, and Jesper Linde (2005) "Firm-Specific Capital, Nominal Rigidities and the Business Cycle," National Bureau of Economic Research Working Paper No. 11034.

[2] Andre, Javier, J. David Lopez-Salido, and Edward Nelson (2005) "Sticky-Price Models and the Natural Rate Hypothesis," *Journal of Monetary Economics*, 52(5), 1025-1053.

[3] Ball, Laurence and David Romer (1990) "Real Rigidities and the Non-Neutrality of Money," *Review of Economic Studies*, 57(2), 183-203.

[4] Blanchard, Olivier J. and Charles M. Kahn (1980) "The Solution of Linear Difference Systems under Rational Expectations," *Econometrica*, 48(5), 1305-1313.

[5] Brock, William A., Steven N. Durlauf, and Kenneth D. West (2003) "Policy Evaluation in Uncertain Economic Environments," *Brookings Papers on Economic Activity*, 1, 235-302.

[6] Calvo, Guillermo A. (1983) "Staggered Prices in a Utility Maximizing Framework," *Journal of Monetary Economics*, 12(3), 383-398.

[7] Chirinko, Robert S. (1993) "Business Fixed Investment Spending: A Critical Survey of Modeling Strategies, Empirical Results and Policy Implications," *Journal of Economic Literature*, 31(4), 1875-1911.

[8] Christiano, Lawrence J. and Martin Eichenbaum (1992) "Current Real-Business Cycle Theories and Aggregate Labor-Market Fluctuations," *American Economic Review*, 82(3), 430-450.

[9] Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans (2005) "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113(1), 1-45.

[10] Clarida, Richard, Jordi Gali, and Mark Gertler (2000) "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115(1), 147–180.

[11] Coibion, Olivier (forthcoming) "Testing the Sticky Information Phillips Curve," *Review of Economics and Statistics*.

[12] Coibion, Olivier and Yuriy Gorodnichenko (2008) "Monetary Policy, Trend Inflation and the Great Moderation: An Alternative Interpretation," Manuscript.

[13] Coibion, Olivier and Yuriy Gorodnichenko (2009) "Strategic Interaction Among Heterogenous Price-Setters in an Estimated DSGE model," Manuscript.

[14] Cogley, Timothy and Thomas J. Sargent (2005) "Drifts and Volatilities: Monetary Policies and Outcomes in the Post WWII U.S.," *Review of Economic Dynamics*, 8(2), 262-302.

[15] Cogley, Timothy and Argia M. Sbordone (2008) "Trend Inflation, Indexation, and Inflation Persistence in the New Keynesian Phillips Curve," *American Economic Review*, 98(5), 2101-2126.

[16] Davig, Troy and Taeyoung Doh (2008) "Changes in Inflation Persistence: Lessons from Estimated Markhov-Switching New Keynesian Models," Manuscript, Federal Reserve Bank of Kansas City.

[17] Del Negro, Marco, Frank Schorfheide, Frank Smets, Rafael Wouters (2007) "On the Fit of New Keynesian Models," *Journal of Business and Economic Statistics*, 25(2), 143-162.

[18] Dixit, Avinash and Joseph Stiglitz, 1977, "Monopolistic Competition and Optimum Product Diversity," *American Economic Review*, 67(3), 297-308.

[19] Duffy, John and Jim Engle-Warnick (2006) "Multiple Regimes in U.S. Monetary Policy? A Nonparametric Approach," *Journal of Money, Credit, and Banking*, 38(5), 1363-1377.

[20] Dupor, Bill, Tomiyuki Kitamura, and Takayuki Tsuruga (forthcoming) "Integrating Sticky Prices and Sticky Information," *Review of Economics and Statistics.*

[21] Eichenbaum, Martin and Jonas M.D. Fisher (2007) "Estimating the Frequency of Price Re-Optimization in Calvo-Style Models," *Journal of Monetary Economics*, 54(7), 2032-2047.

[22] Erceg, Christopher J., Dale W. Henderson, and Andrew T. Levin (2000) "Optimal Monetary Policy with Staggered Wage and Price Contracts," *Journal of Monetary Economics*, 46(2), 281-313.

[23] Evans, Martin and Paul Wachtel (1993) "Inflation Regimes and the Sources of Inflation Uncertainty," *Journal of Money, Credit, and Banking*, 25(3 Part 2), 475-511.

[24] Hamilton, James D. (1994) *Time Series Analysis*, Princeton: Princeton University Press.

[25] Ireland, Peter N. (2001) "Sticky-Price Models of the Business Cycle: Specification and Stability," *Journal of Monetary Economics*, 47(1), 3-18.

[26] Ireland, Peter N. (2003) "Endogenous Money or Sticky Prices?" *Journal of Monetary Economics*, 50(8), 1623-1648.

[27] Ireland, Peter N. (2004) "Technology Shocks in the New Keynesian Model," *Review of Economics and Statistics*, 86(4), 923–936.

[28] Ireland, Peter N. (2007) "Changes in the Federal Reserve's Inflation Target: Causes and Consequences," *Journal of Money, Credit, and Banking*, 39(8), 1851–1882.

[29] Keen, Benjamin D. (2007) "Sticky Price and Sticky Information Price-Setting Models: What is the Difference?" *Economic Inquiry*, 45(4), 770–786.

[30] Keen, Benjamin D. (forthcoming) "The Signal Extraction Problem Revisited: A Note on its Impact on a Model of Monetary Policy," *Macroeconomic Dynamics*.

[31] Kiley, Michael T. (2007) "A Quantitative Comparison of Sticky-Price and Sticky-Information Models of Price Setting," *Journal of Money, Credit, and Banking*, 39(s1), 101–125.

[32] King, Robert G. and Mark Watson (1998) "The Solution of Singular Linear Difference Systems Under Rational Expectations," *International Economic Review*, 39(4), 1015-1026.

[33] King, Robert G. and Mark Watson (2002) "System Reduction and Solution Algorithms for Singular Linear Difference Systems Under Rational Expectations," *Computational Economics*, 20(1-2), 57-86.

[34] Koenig, Evan F. (1996) "Aggregate Price Adjustment: The Fischerian Alternative," Federal Reserve Bank of Dallas Working Paper #9615.

[35] Koenig, Evan F. (1999) "A Fischerian Theory of Aggregate Supply," Manuscript, Federal Reserve Bank of Dallas.

[36] Koenig, Evan F. (2000) "Is There a Persistence Problem? Part 2: Maybe Not," Federal Reserve Bank of Dallas *Economic Review*, Quarter 4, 11-19.

[37] Korenok, Oleg (2008) "Empirical Comparison of Sticky Price and Sticky Information Models," *Journal of Macroeconomics*, 30(3), 906-927.

[38] Laforte, Jean-Philippe (2007) "Pricing Models: A Bayesian DSGE Approach for the U.S. Economy," *Journal of Money, Credit, and Banking*, 39(s1), 127-154.

[39] Lansing, Kevin J. (2009) "Time-Varying U.S. Inflation Dynamics and the New Keynesian Phillips Curve," *Review of Economic Dynamics*, 12(2), 304-326.

[40] Mankiw, N. Gregory and Ricardo Reis (2002) "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics*, 117(4), 1295-1328.

[41] Mankiw, N. Gregory and Ricardo Reis (2007) "Sticky Information in General Equilibrium," *Journal of the European Economics Association*, 5(2-3), 603-613.

[42] McCallum, Bennett T. and Edward Nelson (1999) "An Optimizing IS-LM Specification for Monetary Policy and Business Cycle Analysis," *Journal of Money, Credit, and Banking*, 31(3), 296-316.

[43] McConnell, Margaret M. and Gabriel Perez-Quiros (2000) "Output Fluctuations in the United States: What Has Changed Since the Early 1980s," *American Economic Review*, 90(5), 1464-1476.

[44] Piger, Jeremy M. (2008) "Bayesian Model Averaging for Multiple Structural Change Models," Manuscript, University of Oregon.

[45] Sims, Christopher (2002) "Solving Linear Rational Expectations Models," *Computational Economics*, 20(1-2), 1-20.

[46] Smets, Frank and Rafael Wouters (2003) "An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area," *Journal of the European Economics Association*, 1(5), 1123-1175.

[47] Stock, James H. and Mark W. Watson (2007) "Why Has U.S. Inflation Become Harder to Forecast?" *Journal of Money, Credit, and Banking*, 39(s1), 3-33.

[48] Taylor, John B. (1993) "Discretion Versus Policy Rules in Practice," *Carnegie-Rochester Conference Series on Public Policy*, 39(1), 195-214.

[49] Wang, Pengfei and Yi Wen (2006) "Solving Linear Difference Systems with Lagged Expectations by a Method of Undetermined Coefficients," Federal Reserve Bank of St. Louis Working Paper #2006-003.

Table 1: Estimating the Inflation Process

Panel A: Quandt-Andrews Test

h	Trim	Most Likely Break	Max F-Statistic	P-Value
1	25%	1968:Q3	7.184	0.203
2	25%	1981:Q2	10.575	0.053
3	25%	1981:Q3	11.351	0.038
4	25%	1981:Q3	15.529	0.006

Panel B: Estimation Results

	1969:Q3-1981:Q2				1981:Q3-2006:Q4			
h	α_1	$(1-\alpha_1)$	Adj. R^2	S. E.	α_1	$(1-\alpha_1)$	Adj. R^2	S. E.
1	0.150	0.850	0.065	1.606	0.316	0.684	0.188	0.880
	(0.052)	(0.052)			(0.064)	(0.064)		
2	0.159	0.841	0.062	1.717	0.422	0.578	0.345	0.907
	(0.057)	(0.057)			(0.057)	(0.057)		
3	0.187	0.813	0.067	1.905	0.469	0.531	0.483	0.863
	(0.065)	(0.065)			(0.048)	(0.048)		
4	0.171	0.829	0.056	1.872	0.483	0.517	0.549	0.830
	(0.064)	(0.064)			(0.043)	(0.043)		

Table 2: Estimating the Predictive Power of Expected Inflation

Panel A: Quandt-Andrews Test

h	Trim	Most Likely Break	Max F-Statistic	P-Value
1	25%	1985:Q3	1.414	0.818
2	25%	1979:Q1	1.354	0.835
3	25%	1990:Q1	1.771	0.716
4	25%	1987:Q1	2.636	0.505

Panel B: Estimation Results

	1969:Q3-1981:Q2				1981:Q3-2006:Q4			
h	α_1	$(1-\alpha_1)$	Adj. R^2	S. E.	α_1	$(1-\alpha_1)$	Adj. R^2	S. E.
1	0.695	0.305	0.352	1.470	0.622	0.378	0.266	0.837
	(0.137)	(0.137)			(0.102)	(0.102)		
2	0.372	0.628	0.135	1.698	0.421	0.579	0.195	0.877
	(0.137)	(0.137)			(0.084)	(0.084)		
3	0.252	0.748	0.102	1.730	0.309	0.691	0.126	0.913
	(0.108)	(0.108)			(0.080)	(0.080)		
4	0.192	0.808	0.069	1.779	0.229	0.771	0.091	0.932
	(0.103)	(0.103)			(0.071)	(0.071)		

Table 3: Summary Statistics for $\mathbf{SPF}_t(\boldsymbol{\pi}_{t+h})$ (annualized rate)

	1968:Q4-1981:Q2			1981:Q3-2006:Q4		
h	Mean	Median	Stnd. Dev.	Mean	Median	Stnd. Dev.
1	6.280	6.235	2.298	2.976	2.660	1.345
2	5.887	5.960	2.193	3.065	2.570	1.373
3	5.625	5.880	2.027	3.178	2.875	1.317
4	5.544	5.850	1.901	3.263	2.935	1.353

Table 4: Maximum Likelihood Estimates and Standard Errors Sticky Price & Wage Model (Static Indexation)

	1954:Q3-1981:Q2		1981:Q3-2006:Q4	
Parameter	Estimate	Standard Error	Estimate	Standard Error
η_p	0.1026	0.0269	0.2512	0.0727
ϕ_R	0.8373	0.0786	0.8440	0.0349
ϕ_π	0.5981	0.1261	0.6280	0.1062
ϕ_y	0.4730	0.1065	0.3798	0.0762
ρ_Z	0.8332	0.0664	0.9732	0.0409
ρ_a	0.9670	0.0144	0.9056	0.0199
ρ_R	-0.0868	0.0621	-0.1408	0.0670
σ_Z	0.0595	0.0311	0.0084	0.0026
σ_a	0.0770	0.0336	0.0195	0.0037
σ_R	0.0052	0.0011	0.0025	0.0004

Table 5: Maximum Likelihood Estimates and Standard Errors Sticky Price & Wage Model (Dynamic Indexation)

	1954:Q3-1981:Q2		1981:Q3-2006:Q4	
Parameter	Estimate	Standard Error	Estimate	Standard Error
η_p	0.0593	0.0113	0.0559	0.0128
ϕ_R	1.0000	0.1040	0.8904	0.0387
ϕ_π	0.3833	0.1310	0.5137	0.1139
ϕ_y	0.6250	0.1487	0.5123	0.1066
ρ_Z	-0.1533	0.0554	-0.0702	0.0673
ρ_a	0.9830	0.0112	0.9021	0.0201
ρ_R	-0.1260	0.0621	-0.1393	0.0685
σ_Z	0.7821	0.2744	0.4794	0.1924
σ_a	0.1459	0.0848	0.0188	0.0034
σ_R	0.0064	0.0015	0.0031	0.0006

Table 6: Maximum Likelihood Estimates and Standard Errors
Sticky Information Model

	1954:Q3-1981:Q2		1981:Q3-2006:Q4	
Parameter	Estimate	Standard Error	Estimate	Standard Error
η_p	0.1368	0.0539	0.1432	0.0555
ϕ_R	0.9153	0.0854	0.8759	0.0357
ϕ_π	0.7048	0.0589	0.5908	0.0557
ϕ_y	0.7611	0.0568	0.4328	0.0669
ρ_Z	0.8990	0.0317	0.9694	0.0381
ρ_a	0.9726	0.0079	0.9237	0.0047
ρ_R	-0.0903	0.0464	-0.1398	0.0792
σ_Z	0.0181	0.0066	0.0106	0.0038
σ_a	0.0971	0.0231	0.0239	0.0032
σ_R	0.0080	0.0008	0.0027	0.0003

Table 7: Model Comparison

Panel A: 1954:Q3-1981:Q2

	Log-likelihood	BIC	Pseudo-odds measure (1)	(2)	(3)	(4)
Sticky Price & Wage (Static)	1,072.72	1,049.31	0.02	0.02	0.00	0.00
Sticky Price & Wage (Dynamic)	1,081.40	1,057.99	–	–	0.99	0.99
Sticky Information	1,076.68	1,053.27	0.98	0.97	0.01	0.01
VAR, N equals 4	1,094.36	989.86	–	0.00	–	0.00
VAR, N equals 3	1,097.66	1,013.89	–	0.00	–	0.00
VAR, N equals 2	1,095.79	1,032.83	–	0.00	–	0.00
VAR, N equals 1	1,091.19	1,049.13	–	0.02	–	0.00

Panel B: 1981:Q3-2006:Q4

	Log-likelihood	BIC	Pseudo-odds measure (1)	(2)	(3)	(4)
Sticky Price & Wage (Static)	1,174.53	1,151.41	0.61	0.38	0.61	0.38
Sticky Price & Wage (Dynamic)	1,169.09	1,145.96	–	–	0.00	0.00
Sticky Information	1,174.10	1,150.98	0.39	0.25	0.39	0.25
VAR, N equals 4	1,238.45	1,135.29	–	0.00	–	0.00
VAR, N equals 3	1,234.04	1,151.33	–	0.35	–	0.35
VAR, N equals 2	1,210.13	1,147.96	–	0.01	–	0.01
VAR, N equals 1	1,186.71	1,145.17	–	0.00	–	0.00

Table 8: Forecast Error Variance Decompositions
Sticky Price & Wage Model (Static Indexation)

1954:Q3-1981:Q2

Output Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	70.2	42.2	26.9	21.1	16.7	12.4	8.0
Technology	18.1	53.0	70.5	74.8	71.6	55.6	36.2
Aggregate demand	11.8	4.8	2.6	4.1	11.6	32.1	55.8

Inflation Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	4.3	6.4	7.8	7.9	7.5	7.2	7.2
Technology	83.2	72.3	62.3	58.4	56.3	55.0	54.7
Aggregate demand	12.5	21.3	30.0	33.8	36.2	37.8	38.1

Nominal Interest Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	4.0	1.4	0.8	0.7	0.5	0.4	0.4
Technology	0.1	0.1	0.4	0.5	0.5	0.4	0.4
Aggregate demand	96.0	98.5	98.8	98.8	99.0	99.2	99.3

1981:Q3-2006:Q4

Output Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	40.0	16.6	8.5	5.8	3.9	2.6	2.0
Technology	44.6	78.0	89.0	92.1	93.9	95.0	95.5
Aggregate demand	15.4	5.4	2.5	2.1	2.2	2.4	2.5

Inflation Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	11.0	13.1	13.8	13.8	13.7	13.7	13.6
Technology	76.2	68.4	64.9	64.3	64.3	64.4	64.6
Aggregate demand	12.9	18.5	21.4	22.0	22.0	21.9	21.9

Nominal Interest Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	12.2	5.5	3.9	3.4	3.1	3.0	3.0
Technology	6.9	3.3	2.4	2.2	2.3	2.5	2.8
Aggregate demand	80.9	91.3	93.8	94.4	94.6	94.5	94.2

Table 9: Forecast Error Variance Decompositions
Sticky Price & Wage Model (Dynamic Indexation)

1954:Q3-1981:Q2

Output Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	83.9	75.7	60.3	45.7	23.7	8.5	2.8
Technology	2.5	14.1	33.9	43.5	31.7	11.4	3.8
Aggregate demand	13.6	10.3	5.8	10.8	44.6	80.1	93.4

Inflation Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	0.4	4.2	11.6	15.6	15.8	15.4	14.9
Technology	98.7	86.9	61.6	45.3	40.6	41.8	40.7
Aggregate demand	0.8	8.9	26.8	39.1	43.7	42.9	44.4

Nominal Interest Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	0.4	1.8	2.3	2.3	1.9	1.6	1.3
Technology	1.3	2.5	1.3	1.4	2.0	1.8	1.5
Aggregate demand	98.3	95.7	96.4	96.3	96.1	96.7	97.2

1981:Q3-2006:Q4

Output Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	66.0	44.0	27.9	21.1	18.1	17.7	17.4
Technology	13.7	41.9	64.0	73.1	75.4	72.8	72.2
Aggregate demand	20.3	14.1	8.2	5.8	6.6	9.5	10.4

Inflation Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	0.2	2.2	7.3	11.0	10.9	10.7	10.7
Technology	99.6	96.3	87.3	80.7	80.9	81.1	81.1
Aggregate demand	0.2	1.6	5.4	8.3	8.2	8.2	8.2

Nominal Interest Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	2.5	0.9	0.6	0.6	0.5	0.5	0.5
Technology	0.9	0.4	0.4	0.4	0.4	0.4	0.4
Aggregate demand	96.6	98.7	99.0	99.0	99.1	99.1	99.1

Table 10: Forecast Error Variance Decompositions
Sticky Information Model

1954:Q3-1981:Q2

Output Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	82.7	62.8	45.4	34.1	21.6	10.8	4.9
Technology	9.0	33.3	47.8	47.9	37.5	20.5	9.3
Aggregate demand	8.3	3.9	6.8	18.0	41.0	68.7	85.8

Inflation Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	5.3	12.6	16.0	16.1	15.6	15.4	15.3
Technology	92.8	69.3	52.9	49.4	48.6	48.6	48.3
Aggregate demand	1.9	18.1	31.2	34.6	35.8	36.0	36.4

Nominal Interest Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	1.4	0.5	0.3	0.2	0.2	0.1	0.1
Technology	0.5	0.2	0.1	0.1	0.1	0.1	0.1
Aggregate demand	98.1	99.3	99.6	99.7	99.8	99.8	99.8

1981:Q3-2006:Q4

Output Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	51.7	27.7	15.4	10.5	6.6	4.3	3.3
Technology	27.2	62.1	79.8	86.1	90.2	92.3	92.7
Aggregate demand	21.1	10.2	4.8	3.4	3.1	3.5	4.0

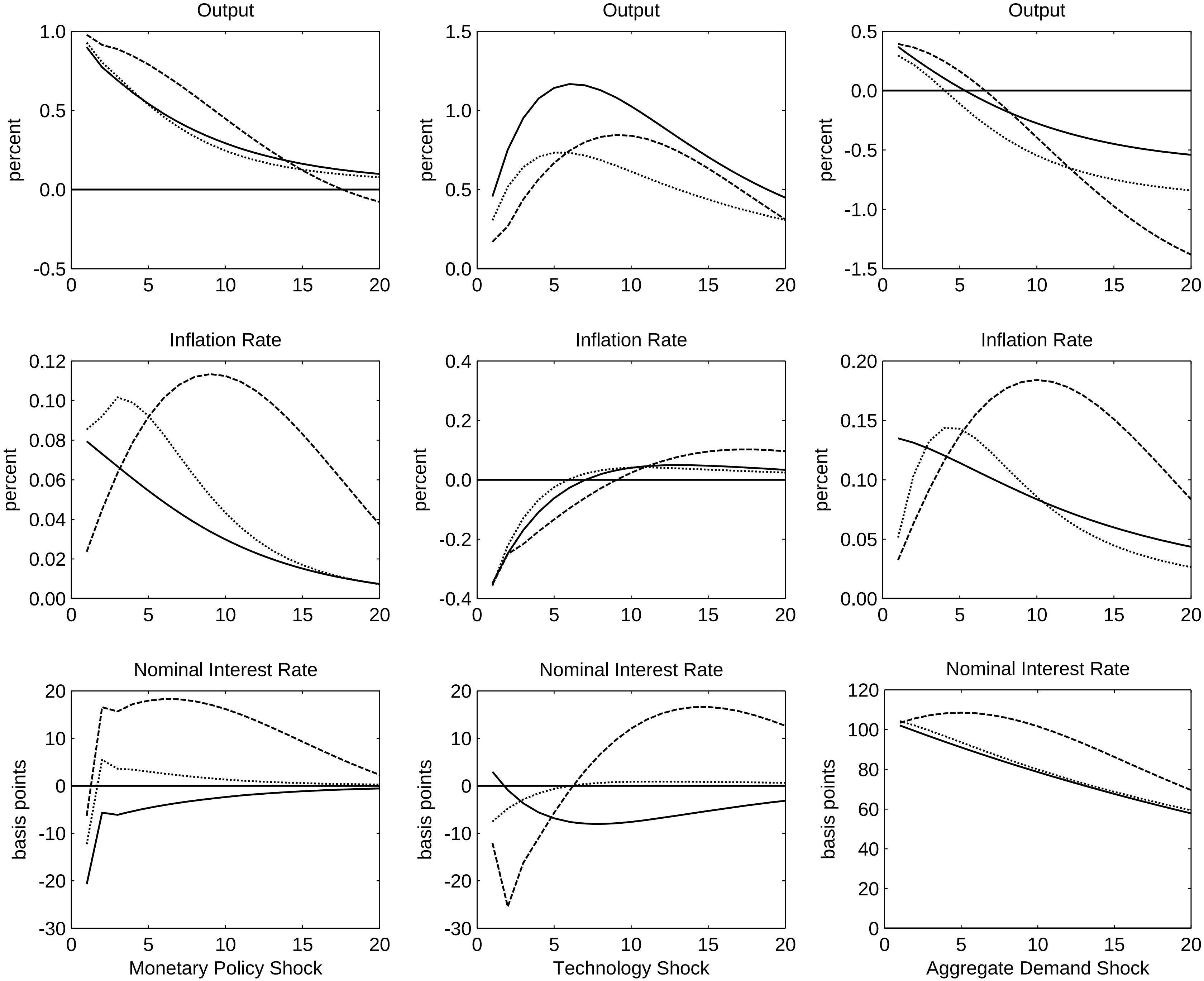
Inflation Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	4.6	6.5	10.6	10.9	10.9	10.8	10.7
Technology	92.5	80.3	73.1	71.5	71.2	71.5	71.7
Aggregate demand	2.9	11.2	16.4	17.6	17.9	17.7	17.6

Nominal Interest Rate Decompositions

Quarters Ahead	1	4	8	12	20	40	∞
Monetary policy	7.1	2.9	2.0	1.7	1.5	1.4	1.4
Technology	2.9	1.5	1.0	0.8	0.8	1.0	1.1
Aggregate demand	90.0	95.7	97.0	97.5	97.7	97.6	97.5

Figure 1: Impulse Responses, 1954:Q3-1981:Q2



Sticky Price & Wage (Static) Sticky Price & Wage (Dynamic) Sticky Information

Figure 2: Impulse Responses, 1981:Q3-2006:Q4