How Robust are Popular Models of Nominal Frictions?*

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Abstract

This paper analyzes various combinations of nominal price and wage frictions to determine which specifications best fit post-war U.S. data. We construct dynamic stochastic general equilibrium (DSGE) models that incorporate those frictions and use Bayesian methods to estimate each model's parameters. Since previous research finds that inflation was unanchored during the 1970s, we divide the data into three distinct periods: the early sample (from the mid-1950s through the 1960s), the middle sample (during the 1970s), and the late sample (from 1983 through 2007). Our estimates indicate that price and wage contracting arrangements have changed over time. Prices are re-optimized more often and exhibit a higher degree of indexation to past inflation in the middle sample than in the other two periods. In contrast, wages are re-optimized more frequently and display less evidence of indexation as time progresses. Our empirical results also suggest that both smaller and less-frequent technology shocks and improved monetary policy contributed to the reduced volatility in output observed during the "Great Moderation" period.

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1 Introduction

1.1 Motivation and Main Results

Recently, economists have enjoyed considerable success constructing and estimating dynamic stochastic general equilibrium (DSGE) models which are competitive with vector autoregressive (VAR) models in their ability to match macroeconomic data.[1] DSGE models are grounded in utility and profit maximization making them robust to changes in the conduct of monetary policy and ideal for comparing the performance of alternative policy rules. The validity of such comparisons is based on the assumption that the utility and profit maximization problems embedded in the models are specified correctly (Del Negro et al., 2007).

It is generally accepted that DSGE models require a mix of nominal and real rigidities in order to produce realistic impulse responses and autocorrelations (Ball and Romer, 1990). Most of the disagreement among economists centers on the nature of the nominal frictions and less on the type of real rigidities.[2] Motivated by the "menu costs" literature, early DSGE models held prices fixed between discrete price adjustment opportunities. In pursuit of plausible qualitative and quantitative results, most models now assume that prices can change every period, but not every price is optimized each period. Those prices and wages that are not optimized increase automatically either by their steady-state inflation rate (static indexation) or by their lagged inflation rate (dynamic indexation). Prices and wages may also change by an amount that is a weighted average of the steady-state and lagged inflation rates (partial indexation). Other researchers assume that optimizing firms and households select the price and wage paths that they follow until their next optimization opportunity (sticky information).

Each type of nominal friction has intuitive appeal under certain circumstances. Adjusting prices or wages by a constant default inflation rate between re-optimization opportunities seems reasonable in a stable-inflation environment; indexing to lagged inflation is plausible when inflation changes are unpredictable; while pre-setting price and wage paths are sensible when inflation is variable, but its movements are predictable. The fact that the economic environment influences the plausibility of each type of price and wage setting leads us to believe one single style of price and wage frictions may not be appropriate in DSGE models that span long periods of time. Specifically, we believe that changes in the conduct of monetary policy can systematically alter the price-setting and wage-setting behaviors of firms and households.[3]

In this paper, we construct a series of DSGE models of the U.S. economy. The models share a common set of assumptions about technology, tastes, market structure, and real-side frictions. They differ, however, in their assumptions about how prices and wages adjust. With four alternative models of price setting and four alternative models of wage setting, we estimate a total of 16 models. To test the robustness of each combination of assumptions,

[1] Frequently cited are Smets and Wouters (2003) and Christiano, Eichenbaum, and Evans (2005).

[2] More recently, economists have begun introducing explicit financial-sector frictions into DSGE models in an effort to better understand the 2008 financial crisis and its aftermath. A prominent example is Christiano, Motto, and Rostagno (2010). Since financial frictions are not vital to our analysis, we end the sample just prior to the financial crisis.

[3] This basic idea goes back to at least Ball, Mankiw, and Romer (1988), who suggest that fixed-price contracts will be updated more frequently as the average inflation rate rises.

we estimate the models over three distinct sample periods: an early sample that stretches from 1955:Q1-1968:Q4, a middle sample that runs from 1969:Q1-1979:Q3, and a late sample that goes from 1983:Q1-2007:Q4.[4] Existing studies (discussed in detail below) show that inflation followed a non-stationary process during our middle sample, and suggest that the non-stationarity was the result of a poorly conceived or badly executed monetary policy. Evidence from our early and late sample periods, in contrast, indicates that monetary policy successfully anchored inflation. By assessing the fit of our alternative price- and wage-setting rules across different sample periods, we test the robustness of those specifications to changes in the conduct of monetary policy. In addition, by comparing models across our early and late sample periods, we can evaluate the models' robustness to important long-run institutional changes in the economy while holding the conduct of monetary policy basically constant. Finally, we briefly compare the size of various economic shocks across sample periods in order to gain some insight into the sources of the reduction in output volatility known as the "Great Moderation."

Previous studies find strong evidence that monetary policy failed to stabilize inflation during the 1970s. Price-setting arrangements adjusted to that policy failure. Specifically, output prices were re-optimized somewhat more frequently during the middle period, and our empirical results indicate that firms moved away from static price indexation and toward partial or dynamic indexation. Wage-setting arrangements, in contrast, appear to be less influenced by the conduct of monetary policy and more influenced by long-term institutional trends such as the shrinking importance of unions and their multi-year labor contracts. We also find that technology shocks had a far larger impact on output volatility during the middle sample than during the early or late samples, and that shocks to the Federal Open Market Committee's (FOMC) target inflation rate contributed much more to output volatility in the early sample than in the middle or late samples. Those results suggest that both luck (*i.e.*, smaller and less frequent technology shocks) and improved monetary policy were proximate causes of the Great Moderation in output volatility observed from the mid-1980s through the mid-2000s.

1.2 Evidence for a 3-Way Sample Split

Evans and Wachtel (1993) present evidence that the behavior of inflation shifted during the 1970s. Specifically, they estimate a two-state, Markov-switching model using quarterly U.S. data from 1955 through 1991, where inflation follows a stationary AR(1) process in one state and a random walk in the other. Their results suggest inflation undergoes a sharp transition from a stationary process to a non-stationary process in 1969 and an equally sharp transition back to a stationary process in 1985.[5] They also find that "Inflation uncertainty increases at all horizons in 1968 and does not return to the low levels of the 1950s and 1960s until 1984" (Evans and Wachtel, 1993, p. 497). Murray, Nikolsko-Rzhevskyy, and Papell (2015), similarly, find that inflation follows a stationary AR(2) process over the periods 1954:Q4-1967:Q2, 1975:Q2-1976:Q3, and 1981:Q2 to the end of their sample in 2007:Q1. During the other periods (1967:Q3-1975:Q1 and 1976:Q4-1981:Q1), their results indicate inflation is

[4] The 1979:Q4-1982:Q4 Volcker monetary policy experiment is simply too short for us to analyze.

[5] Between 1969 and 1985, Evans and Wachtel (1993) find evidence of a few isolated, transitory, state reversals.

non-stationary.[6] Our middle sample period, which runs from 1969:Q1-1979:Q3, is dominated by non-stationary inflation behavior according to both of those studies, whereas our early (1955:Q1-1968:Q4) and late (1983:Q1-2007:Q4) samples are periods during which inflation usually followed a stationary process.

Many papers have concluded that monetary policy mistakes were a major contributor to the elevated inflation rates observed during the 1970s. For example, Clarida, Gali, and Gertler (2000) find that pre-Volcker monetary policy failed to satisfy the Taylor principle that the short-term nominal interest rate responds by more than one-for-one to changes in inflation. Their data covers the 1960:Q1-1996:Q4 period, which they split in 1979:Q3 on a priori grounds. Nikolsko-Rzhevskyy and Papell (2012) estimate Taylor rules with a variety of real-time output-gap measures from 1969:Q1-1979:Q4. They conclude that the Taylor-principle requirement was not satisfied. As a result, monetary policy failed to keep inflation from rising. The authors suggest that policymakers were not aggressive enough when reacting to inflation because they overestimated how much inflation tends to fall during recessions. In hindsight, the FOMC placed too much weight on the output gap, relative to lagged inflation, when formulating policy. Kozicki and Tinsley (2009), who use real-time inflation forecasts and unemployment gap measures to estimate Taylor-rule models with time-varying parameters, also find that the Taylor principle was violated in the 1970s. They attribute that policy failure to the FOMC's weak response to deviations of money growth from target. In addition, they note that the FOMC's policy of targeting money growth during the 1970s unintentionally drove inflation higher when trend output growth and money velocity experienced unobserved shifts.

Cogley and Sargent (2005) examine the joint behavior of inflation, the unemployment rate, and the Federal Reserve's interest-rate policy over a 1959-2000 sample using a VAR with time-varying coefficients and stochastic volatilities. Their analysis shows the inflation rate target was low and reasonably stable from 1959-1966 and again from 1981-2000, but was high and generally rising from 1967-1979.[7][8] Similarly, the estimated persistence of inflation is noticeably higher from 1967-1981 than during either 1959-1966 or 1982-2000. Monetary policy is "activist" (consistent with the Taylor principle) from 1959-1967, either "neutral" or "passive" from 1968-1980, and again activist from 1981-2000.

Wage-setting practices have also experienced significant changes over the 50-plus years of our sample. Figure 1 shows that the percentage of private-sector workers who are union members has declined significantly from 35.1 percent in 1955 (the start of our early sample), to 29.0 percent in 1969 (the start of our middle sample), to 16.5 percent in 1983 (the start of our late sample), and to 7.5 percent in 2007 (the end of our late sample). Furthermore, Figure 2 illustrates that the percentage of private-sector union workers covered by automatic cost-of-living adjustments (COLAs) fell by half from 50 percent in the late 1950s to 25 percent in the late 1960s, then soared to 60 percent by the mid-1970s and through the early 1980s, and eventually fell back down to 22 percent by the mid-1990s, when the government last compiled

[6] In the same vein, Piger (2008) finds that inflation persistence was elevated from the late 1960s through 1981. Levin and Piger (2008), although failing to find compelling evidence of a shift in inflation persistence, document a period of sharply elevated inflation uncertainty between 1969 and 1981.

[7] 1980 was a transition year during which the target inflation rate began to fall but remained elevated.

[8] "Target inflation" is technically a long-horizon inflation forecast. Cogley and Sargent (2005) call it "core inflation."

the data.[9] Given that employment in unionized industries is typically governed by multi-year contracts, one might reasonably expect declines in union density to be associated with increases in the average frequency with which wages are re-optimized. Similarly, changes in the prevalence of COLA provisions likely signal corresponding changes in the prevalence of dynamic or partial indexation in the intervals between each union contract negotiation.

To summarize, the literature has uncovered considerable evidence that price inflation began to follow a non-stationary process during the late 1960s, and that the shift in inflation behavior was the result of a poorly conceived and/or executed monetary policy. In response to high, rising, and uncertain inflation, COLA provisions became more common in labor contracts. An activist monetary policy re-established inflation control in the early to mid-1980s. Those findings suggest that the 1970s provide a useful test of the robustness of alternative models of nominal frictions to a substantial change in monetary policy. Moreover, any DSGE model that combines 1970s data with data from the decades immediately before or afterward risks generating spurious results.

1.3 Relationship to the Existing Literature

This paper differs from the existing DSGE literature in both the wide range of nominal frictions examined and our strategy to estimate and analyze those nominal frictions over three distinct sample periods. Many researchers either estimate their models over a single sample period which corresponds, roughly, to our late sample, or compare results from late-sample estimates with full-sample estimates. A few others separately analyze early- and late-sample estimates, but we are unaware of any previous study that uses a three-way sample split. As for the type of nominal frictions examined: Few studies include sticky information models in their comparisons because those models contain a large number of state variables and, consequently, are complicated to estimate. Table 1 gives a list of prominent papers on this topic. Although nominal wage rigidities are crucial for realistic model performance (Christiano, Eichenbaum, and Evans, 2005), most studies comparing nominal frictions do not explicitly consider them. Sometimes wage frictions are incorporated by assuming that the economy consists of independent yeoman farmers who produce differentiated intermediate goods that are each subject to price frictions.[10] We conclude that existing dynamic macro studies are not structured in a way that enables them to examine how price-setting and wage-setting arrangements responded to the monetary policy failure of the 1970s.

1.4 Outline

The remainder of the paper is structured as follows. Section 2 outlines our DSGE model, including the different specifications of price and wage rigidities. Section 3 discusses our estimation procedure. Section 4 presents the posterior probabilities attached to the different models of price and wage frictions in each sample period and discusses the parameter

[9] Blanchard and Gali (2009, p. 396) in their examination of the impact of oil-price shocks on macroeconomic conditions note that "The 1970s were times of strong unions and high wage indexation. In the 2000s, unions are much weaker, and wage indexation has practically disappeared."

[10] Koenig (2000) and Edge (2002) highlight that this is mathematically equivalent to introducing wage frictions. For background, see Koenig (1999) and Chari, Kehoe, and McGrattan (2000).

estimates obtained for the highest-probability model in each period. Section 5 considers the models' empirical implications, presenting variance decompositions, historical output decompositions, and impulse response functions. Section 6 summarizes our main findings and offers suggestions for future research.

2 The Models

We use a conventional 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 four alternative types of nominal wage and price rigidities which are interchanged to produce 16 different models for empirical evaluation. In particular, we consider sticky price and sticky wage specifications with static indexation, partial indexation, and dynamic indexation, and a sticky information specification for price and wage setting. The models include eight exogenous stochastic processes representing multifactor technology, marginal efficiency of investment, preferences, government spending, price markup, wage markup, the inflation target, and the monetary authority's policy rate stance. We then proceed to estimate those models with data on output, consumption, investment, labor hours, the real wage, inflation, and the nominal interest rate.

2.1 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:

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

where E_t is the expectations operator at time t, β is the personal discount factor with a value between 0 and 1, b is the internal habit persistence parameter and is also between 0 and 1, χ_m and χ_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 a preference shock which evolves according to an autoregressive process of order 1 (*i.e.*, AR(1)):

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

where $0 \leq \rho_a < 1$ and $\varepsilon_{a,t} \sim N(0, \sigma_a)$.[11] Although household h has pricing power in the labor market, nominal wage frictions prevent it from either optimally setting a new wage

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

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 all of the households make identical decisions on their remaining choice variables.[12]

Household h begins each period with its nominal money balances, M_{t-1}, carried over from last period and the principal 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. In addition, household h receives dividends, D_t, from its ownership interest in the firms, a transfer, T_t, equal to a payment from the monetary authority minus lump-sum taxes paid to the government, and a payment, $A_{h,t}$, from its participation in the state-contingent securities market. Those assets are utilized to purchase goods for consumption and investment, i_t, and to finance end-of-period money and bond holdings. The flow of funds for household h is described by the following budget constraint:

$$P_t(c_t + i_t) + M_t + B_t = M_{t-1} + R_{t-1}B_{t-1} + W_{h,t}n_{h,t} + P_t q_t k_t + D_t + T_t + A_{h,t}. \tag{2}$$

Investment purchases in (2) are converted into capital according to the equation:

$$k_{t+1} - k_t = J_t i_t \left[1 - S\left(\frac{i_t}{i_{t-1}}\right)\right] - \delta k_t, \tag{3}$$

where δ is the depreciation rate. The variable, J_t, is a Greenwood et al. (1988) shock to the marginal efficiency of investment that follows an AR(1) process:

$$\ln(J_t) = \rho_J \ln(J_{t-1}) + \varepsilon_{J,t},$$

where $0 \leq \rho_J < 1$ and $\varepsilon_{J,t} \sim N(0, \sigma_J)$. The functional form $S(\cdot)$ in (3) represents the adjustment costs associated with changing the level of investment. The average and marginal investment adjustment costs are zero around the steady state (*i.e.*, $S(1) = S'(1) = 0$), whereas the convexity of the investment adjustment costs imply that $\kappa \equiv S''(1) > 0$.[13]

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:

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

where $\theta_{w,t}$ is a stochastic parameter which determines the time-varying markup of wage over the marginal rate of substitution. Following Smets and Wouters (2007), we assume that $\theta_{w,t}$

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

[13] These assumptions are consistent with the investment adjustment costs specification in Christiano, Eichenbaum, and Evans (2005).

follows an ARMA(1,1):

$$\ln(\theta_{w,t}/\theta_w) = \rho_w \ln(\theta_{w,t-1}/\theta_w) + \varepsilon_{w,t} - \mu_w \varepsilon_{w,t-1},$$

where $0 \leq \rho_w < 1$, $0 \leq \mu_w < 1$, and $\varepsilon_{w,t} \sim N(0, \sigma_w)$. The wage markup process includes a moving average (MA) term to capture some of the high frequency movements in the real wage observed in the data. In our setup, a negative shock to $\theta_{w,t}$ (*i.e.*, $\varepsilon_{w,t} < 0$) is considered a positive wage markup shock because it pushes up the markup of the real wage, $\theta_{w,t}/(\theta_{w,t}-1)$, over the marginal rate of substitution. The demand by firms for household h's labor services is a decreasing function of household h's relative wage:

$$n_{h,t} = \left(\frac{W_{h,t}}{W_t}\right)^{-\theta_{w,t}} n_t, \tag{4}$$

where W_t is interpreted as the aggregate nominal wage:

$$W_t = \left[\int_0^1 {W_{h,t}}^{1-\theta_{w,t}} dh\right]^{1/(1-\theta_{w,t})}. \tag{5}$$

2.1.1 Nominal Wage Frictions

Wage setting is examined in both a sticky wage and sticky information framework. In the sticky wage specification, household h is periodically provided with an opportunity to negotiate a new nominal wage contract. If that opportunity is not available, household h indexes its nominal wage to one of the following three variables: the current steady-state inflation rate, last period's inflation rate, or a weighted average of the steady-state inflation rate and last period's inflation rate. The sticky information friction, on the other hand, allows household h to select a new nominal wage every period, but the information used to set that wage updates infrequently.

Sticky Wages: In our model with wage stickiness, household h sets its nominal wage according to a Calvo (1983) model of random adjustment. Each period, the probability that household h can optimally adjust its nominal wage is η_w. If household h cannot optimally reset its nominal wage, the household automatically adjusts its wage using an index variable. Since the literature is unsettled on the appropriate type of indexation, we consider the three most popular types: partial, static, and dynamic indexation. Partial indexation, as in Smets and Wouters (2003, 2007) and Del Negro et al. (2007), allows non-adjusting households to increase their wage by a weighted average of the current steady-state inflation rate, π^{ss}, and last period's inflation rate, π_{t-1}, where the weights are $(1-\gamma_w)$ and γ_w, respectively.[14] Static indexation, which is used by Erceg, Henderson, and Levin (2000), assumes that a non-adjusting household raises its wage by the current steady-state inflation rate ($\gamma_w = 0$), while dynamic indexation, as in Christiano, Eichenbaum, and Evans (2005), requires nominal wages to increase by last period's inflation rate ($\gamma_w = 1$). When household h has an opportunity to optimally adjust its nominal wage, it selects a wage that maximizes the

[14] Eichenbaum and Fisher (2007) introduce the terminology "static" and "dynamic" indexation to describe the automatic adjustment of wages or prices which cannot be re-optimized in a given period, while Smets and Wouters (2003) define the term "partial" indexation.

present value of its current and expected future utility, (1), subject to its budget constraint, (2), the firms' demand for its labor, (4), and the probability $(1-\eta_w)^j$ that another wage re–optimizing opportunity will not occur in the subsequent j periods. The New Keynesian Wage Phillips Curve with indexation can be easily obtained using the first-order condition from the household's wage-setting problem and the aggregate nominal wage equation, (5):

$$\Delta\widehat{W}_t - \gamma_w\widehat{\pi}_{t-1} = \kappa_w\left(\zeta\widehat{n}_t - \widehat{\lambda}_t + \widehat{a}_t - \frac{\widehat{\theta}_{w,t+j}}{\theta_w - 1} - \widehat{w}_t\right) + \beta E_t\left[\Delta\widehat{W}_{t+1} - \gamma_w\widehat{\pi}_t\right],$$

where λ_t is the marginal utility of consumption, w_t is the real wage, a hat symbol, "^", indicates the percent deviation of a variable from its steady state, $\Delta\widehat{W}_t = \widehat{w}_t - \widehat{w}_{t-1} + \widehat{\pi}_t$, and $\kappa_w = \eta_w[1-\beta(1-\eta_w)]/[(1-\eta_w)(1+\zeta\varepsilon_w)]$.

Sticky Information Wages: Sticky information is examined in Koenig (1996, 1999, 2000) as a source of wage frictions in the labor market. In that framework, 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, (1), subject to its budget constraint, (2), and the firms' demand for its labor, (4), given that its expectations were last updated j periods ago. When the resulting first-order condition is combined with the aggregate nominal wage equation, (5), we get the Sticky Information Wage Phillips Curve:

$$\Delta\widehat{W}_t = \left(\frac{\eta_w}{1-\eta_w}\right)(\widehat{w}_t^* - \widehat{w}_t) + \sum_{j=0}^{\infty}\eta_w(1-\eta_w)^j E_{t-j-1}\left[\widehat{w}_t^* - \widehat{w}_{t-1}^* + \widehat{\pi}_t\right],$$

where $\widehat{w}_t^* = \left(\widehat{\lambda}_t + \widehat{\theta}_{w,t}/(\theta_w - 1) - \zeta\theta_w\widehat{w}_t - \zeta\widehat{n}_t - \widehat{a}_t\right)/(1+\zeta\theta_w)$.

2.2 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 multifactor technology, Z_t, are utilized by firm f to produce its output, $y_{f,t}$, according to a Cobb-Douglas production function:

$$y_{f,t} = Z_t(k_{f,t})^\alpha(n_{f,t})^{1-\alpha}, \tag{6}$$

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

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

where Z is the steady-state value of Z_t, $0 \le \rho_Z < 1$, and $\varepsilon_{Z,t} \sim N(0,\sigma_Z)$.[15] As a profit-maximizing agent, firm f minimizes its production costs subject to (6). The resulting labor and capital factor demands equal:

$$\psi_t(1-\alpha)Z_t[k_{f,t}/n_{f,t}]^\alpha = w_t, \tag{7}$$

[15] The term $\ln(Z_t/Z)$ is equivalent to the percent deviation of Z_t from its steady state, Z.

$$\psi_t \alpha Z_t [n_{f,t}/k_{f,t}]^{1-\alpha} = q_t, \tag{8}$$

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 (7) and (8):

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

Given that the real wage, real rental rate of capital, and the level of multifactor 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

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

where $\theta_{p,t}$ is a stochastic parameter which determines the time-varying markup of price over real marginal cost. Following Smets and Wouters (2007), we assume that $\theta_{p,t}$ follows an ARMA(1,1):

$$\ln(\theta_{p,t}/\theta_p) = \rho_p \ln(\theta_{p,t-1}/\theta_p) + \varepsilon_{p,t} - \mu_p \varepsilon_{p,t-1},$$

where $0 \leq \rho_p < 1$, $0 \leq \mu_p < 1$, and $\varepsilon_{p,t} \sim N(0, \sigma_p)$. The MA term is incorporated in the price markup process to pick up some of the high frequency movements in inflation observed in the data. In our framework, a negative shock to $\theta_{p,t}$ (*i.e.*, $\varepsilon_{p,t} < 0$) is considered a positive price markup shock because it pushes up the markup of the price, $\theta_{p,t}/(\theta_{p,t}-1)$, over the real marginal cost. Cost minimization by the households generates the following demand equation for firm f's good:

$$y_{f,t} = \left(\frac{P_{f,t}}{P_t} \right)^{-\theta_{p,t}} y_t, \tag{9}$$

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

$$P_t = \left[\int_0^1 P_{f,t}^{1-\theta_{p,t}} df \right]^{1/(1-\theta_{p,t})}. \tag{10}$$

2.2.1 Price Frictions

As in the case of wage setting, we investigate both sticky price and sticky information price-setting rules. The sticky price specification assumes that a random fraction of firms can adjust their prices in any given period. The remaining firms increase their prices by the current steady-state inflation rate, last period's inflation rate, or a weighted average of the steady-state inflation rate and last period's inflation rate. In the sticky information case, prices are flexible, but firms only intermittently update the information used to set those prices.

Sticky Prices: Price-setting behavior follows a Calvo (1983) model of random adjustment, where η_p is the probability that a firm can optimally adjust its price. Since opinions differ on how prices change for the $(1-\eta_p)$ fraction of firms which cannot optimally adjust their price, we again consider partial, static, and dynamic indexation. With partial indexation, a non-price optimizing firm indexes its price with a weight of $(1-\gamma_p)$ on the current steady-state inflation rate, π^{ss}, and a weight of γ_p on last period's inflation rate, π_{t-1}. Static indexation, on the other hand, assumes that a non-optimizing firm raises its price only by the current steady-state inflation rate ($\gamma_p = 0$), whereas dynamic indexation bases the automatic price change on just last period's inflation rate ($\gamma_p = 1$). When given the opportunity to optimally reset its price, a firm selects a price which maximizes its present value of current and expected future profits subject to its factor demand equations, (7) and (8), households' demand for its goods, (9), and the probability, $(1-\eta_p)^j$, that another price adjustment opportunity will not occur in the subsequent j periods. By linearizing the resulting efficiency condition around its steady state, we can easily derive the New Keynesian Price Phillips Curve with indexation:

$$\widehat{\pi}_t - \gamma_p \widehat{\pi}_{t-1} = \left(\frac{\eta_p(1-\beta(1-\eta_p))}{1-\eta_p}\right)\left(\widehat{\psi}_t - \frac{\widehat{\theta}_{p,t}}{(\theta_p - 1)}\right) + \beta\left(E_t(\widehat{\pi}_{t+1}) - \gamma_p \widehat{\pi}_t\right). \tag{11}$$

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 the information used by firms to set those prices adjusts infrequently. In particular, a firm'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, a firm sets a price which maximizes its expected profits subject to its factor demand equations, (7) and (8), and households' demand for its goods, (9). The Sticky Information Price Phillips Curve then is obtained by combining the linearized versions of the firms' first-order condition from its pricing problem and the price aggregation equation, (10):

$$\widehat{\pi}_t = \left(\frac{\eta_p}{1-\eta_p}\right)\left(\widehat{\psi}_t - \frac{\widehat{\theta}_{p,t}}{\theta_p - 1}\right) + \sum_{j=0}^{\infty} \eta_p (1-\eta_p)^j E_{t-j-1}\left[\widehat{\pi}_t + \widehat{\psi}_t - \widehat{\psi}_{t-1} - \frac{\widehat{\theta}_{p,t} - \widehat{\theta}_{p,t-1}}{\theta_p - 1}\right].$$

2.3 Government

The monetary authority utilizes a generalized version of the nominal interest rate rule outlined in Taylor (1993). Specifically, the current nominal interest rate responds to the one- and two-quarter lags of the nominal interest rate, the current year-over-year gross inflation rate, $\Pi_t = P_t/P_{t-4}$, and the current one- and four-quarter growth rates of output:

$$\begin{aligned} \ln(R_t) \;&=\; \phi_{R_1}\ln(R_{t-1}) + \phi_{R_2}\ln(R_{t-2}) + (1-\phi_{R_1}-\phi_{R_2})\left(\ln(r) + \frac{\ln(\Pi_t)}{4}\right) \\ &\quad + \frac{\phi_\pi}{4}\ln\left(\frac{\Pi_t}{\Pi_t^*}\right) + \phi_{\Delta y_1}\ln\left(\frac{y_t}{y_{t-1}}\right) + \frac{\phi_{\Delta y_4}}{4}\ln\left(\frac{y_t}{y_{t-4}}\right) + \varepsilon_{R,t}, \end{aligned}$$

where r is the steady-state real interest rate, the parameters ϕ_{R_1}, ϕ_{R_2}, ϕ_π, $\phi_{\Delta y_1}$, and $\phi_{\Delta y_4}$ are non-negative such that $0 \le \phi_{R_1} + \phi_{R_2} < 1$, and the policy rate disturbance behaves such that

$\varepsilon_{R,t} \sim N(0, \sigma_R)$.[16] The parameter Π_t^* is calculated as the sum of the monetary authority's quarterly inflation rate targets over the previous year (*i.e.*, $\ln(\Pi_t^*) = \ln(\pi_t^*) + \ln(\pi_{t-1}^*) + \ln(\pi_{t-2}^*) + \ln(\pi_{t-3}^*)$), where π_t^* is the gross quarterly inflation rate target. The inflation rate target follows an AR(1) process such that

$$\ln(\pi_t^*) = \rho_\pi \ln(\pi_{t-1}^*) + (1 - \rho_\pi)\ln(\pi^{ss}) + \varepsilon_{\pi,t},$$

where $0 \leq \rho_\pi \leq 1$ and $\varepsilon_{\pi,t} \sim N(0, \sigma_\pi)$.

Real government spending, g_t, is financed via lump-sum taxes on the households. Government spending's share of output, g_t/y_t, evolves as follows:

$$g_t/y_t = (1 - 1/G_t)$$

such that parameter G_t follows an autoregressive process:

$$\ln(G_t) = \rho_G \ln(G_{t-1}) + (1 - \rho_G)\ln(G) + \varepsilon_{G,t},$$

where $G > 0$, $0 < \rho_G < 1$, and $\varepsilon_{G,t} \sim N(0, \sigma_G^2)$. A positive shock to G_t (*i.e.*, $\varepsilon_{G,t} > 0$) is a positive government spending shock because it raises government spending's share of output, g_t/y_t. Finally, the goods market is in equilibrium when the sum of consumption, investment, and government spending equals output:

$$c_t + i_t + g_t = y_t.$$

3 Equilibrium and Estimation Procedure

Our DSGE model is examined with the four different wage-setting and four different price-setting specifications. Wage setting by households exhibits one of the following characteristics: sticky wages with static indexation ($\gamma_w = 0$), sticky wages with partial indexation ($0 < \gamma_w < 1$), sticky wages with dynamic indexation ($\gamma_w = 1$), or sticky information wages. Similarly, firm price setting behaves in one of the following four ways: sticky prices with static indexation ($\gamma_p = 0$), sticky prices with partial indexation ($0 < \gamma_p < 1$), sticky prices with dynamic indexation ($\gamma_p = 1$), or sticky information prices. Since the manner of nominal wage setting can differ from the manner of price setting, we examine every combination of wage and price frictions for a total of 16 different models.

We estimate our 16 models over three distinct time periods: 1955:Q1-1968:Q4, 1969:Q1-1979:Q3, and 1983:Q1-2007:Q4; and then evaluate which model best fits the data over each sample. Selection of those particular time periods is discussed in Section 1.2 and is based on previous studies that indicate inflation followed a stationary process in the early and late samples but a non-stationary process in the middle sample. In each sample period, our model is estimated using U.S. data on output, consumption, investment, the real wage rate, labor hours, inflation, and the nominal interest rate. Output is the chain-weight measure of gross domestic product, consumption is real personal consumption of nondurable goods

[16] Since R_t is specified as a quarterly rate and Π_t and y_t/y_{t-4} as annualized rates, we divide the coefficients on inflation and the four-quarter output growth rate by 4.

and services, and investment is real gross private domestic investment plus real personal consumption of durable goods. The real wage rate is business-sector compensation per hour divided by the gross domestic product implicit price deflator, while hours worked is total hours of nonfarm payrolls. Output, consumption, investment, and labor hours are expressed in per capita terms by dividing by the civilian, noninstitutional population, age 16 and over. To eliminate the long-run growth component, the output, consumption, investment, and real-wage series are linearly detrended by their respective average quarterly growth rates over the estimated sample period. 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.

The equations outlined above for the households, firms, and monetary authority sectors form a system of equations for our models. The presence of a positive steady-state inflation rate, however, requires us to divide the nominal variables $P_{f,t}$, W_t, $W_{h,t}$, $A_{h,t}$, T_t, M_t, B_t, and D_t by the price level, P_t, to induce stationarity. In addition, our model assumes the inflation target, π_t^*, has a unit root in the middle sample (1969:Q1-1979Q3), whereas in the early (1955:Q1-1968:Q4) and late (1983:Q1-2007:Q4) samples the inflation target is stationary.[17] The unit root process in π_t^* then is transferred to the nominal interest rate, R_t, and the inflation rate, π_t, so we induce a stationary process by dividing those variables by π_t^* and setting $\Delta\pi_t^* = \pi_t^*/\pi_{t-1}^*$. For consistency with those transformed definitions for R_t and π_t, data on changes in (rather than the levels of) the nominal interest rate and the inflation rate is utilized when estimating our middle-sample models.

Once the appropriate variables are transformed and the steady state is determined, the system of equations for each model is log-linearized around its steady state. The rational expectations solution can be obtained for all 16 models by utilizing traditional solution methods, such as Blanchard and Kahn (1980), King and Watson (1998, 2002), or Sims (2002). Each model's rational expectations solution is transformed into a state-space system and the Kalman filter is utilized to calculate the likelihood function, $p(\mathbf{Y}_T|\Theta)$, where $\mathbf{Y}_T$ is a matrix of data, and Θ is a vector of parameters. In contrast to maximum likelihood estimation, the Bayesian approach incorporates our beliefs about the parameters before estimation via the specification of prior distributions, $p(\Theta)$, for our model's parameters. Specifically, the likelihood function is combined with the prior distributions to form the posterior distribution, $p(\Theta|\mathbf{Y}_T)$:

$$p(\Theta|\mathbf{Y}_T) \propto p(\mathbf{Y}_T|\Theta)p(\Theta).$$

The posterior function is optimized with respect to Θ to determine the estimated posterior mode for the model's parameters, $\widehat{\Theta}$. The standard errors for $\widehat{\Theta}$ are simply the diagonal elements of the corresponding Hessian matrix evaluated at $\widehat{\Theta}$. The Metropolis-Hastings sampling algorithm is then used to obtain information on the posterior distribution.[18]

[17] If we assume the inflation target follows a stationary process ($\rho_\pi < 1$) over the middle sample, our estimates of ρ_π are extremely close to 1 (usually $\rho_\pi > 0.99$).

[18] Dynare is used for all of our estimation. For the Metropolis-Hastings procedure, we draw 250-thousand times from a model's posterior distribution and discard the first 50-thousand draws. A step size of 0.35 is used which results in an acceptance rate of around 25 percent.

4 Estimation Results and Model Comparisons

4.1 Prior Distributions

Although we estimate our model with seven different data series, five parameters are either unidentified or weakly identified and must be specified prior to estimation. To begin, the quarterly depreciation rate, δ, and discount rate, β, are set equal to 0.025 and 0.99, respectively. The steady-state price elasticity of demand, θ_p, and the steady-state wage elasticity of labor demand, θ_w, are each assumed to equal 6, which is consistent with Erceg, Henderson, and Levin's (2000) assumption that the price and wage markups average 20 percent. Finally, reflecting the fact that our model is a closed-economy, we set government spending's average output share, g/y, equal to one minus the sum of consumption's and investment's average shares. Specifically, g/y equals 25.3 percent in the early sample, 21.7 percent in the middle sample, and 16.8 percent in the late sample. The decline in g/y reflects the fall (ultimately to a negative value) in net exports' share of output in U.S. data.

Each version of our model has between 27 and 30 estimated parameters, with the exact number depending on the sample and specific assumptions about price and wage adjustment. Table 2 includes a complete list of those parameters and their assumed prior distributions, most of which are similar to priors commonly used in the literature. Capital's share of output, α, is normally distributed with a mean of 0.3 and a standard deviation of 0.05, while the degree of habit persistence in consumption, b, follows a beta distribution with mean and standard deviation equal to 0.7 and 0.15, respectively. Consistent with estimates in Christiano, Eichenbaum, and Evans (2005), the degree of curvature in the investment-cost function, κ, is assumed to have a beta distribution with a mean of 4.0 and a standard deviation of 1.5. Given that estimates of the labor-supply elasticity range from 0 to ∞, we transform the inverse of the elasticity of labor supply with respect to the real wage, ζ, so that $1/(\zeta+1)$ follows a beta distribution with a mean of 0.75 (consistent with a labor-supply elasticity equal to 3.0) and a standard deviation of 0.15. The probabilities of wage and price adjustment, η_w and η_p, respectively, have a beta distribution prior with a 0.25 mean (consistent with wages and prices adjusting, on average, once a year) and a 0.1 standard deviation. In those variants of the model with partial indexation of wages and/or prices, the parameters γ_w and γ_p follow a beta distribution with a 0.5 mean and a 0.2 standard deviation.

As previously discussed, our research is motivated in part by evidence that the conduct of monetary policy has varied over time, and by concerns that wage and price adjustment may have responded to shifts in the conduct of that policy. To make allowance for changes in the behavior of the FOMC, we adopt a fairly general Taylor (1993) rule specification and put uniform prior distributions on all of its parameters. Specifically, the uniform prior is defined over the interval $[-2, 2]$ for ϕ_{R_1} and ϕ_{R_2}, $(0, 2]$ for ϕ_π, and $[-1, 1]$ for $\phi_{\Delta y_1}$ and $\phi_{\Delta y_4}$. When estimating models in the early sample, an identification problem exists between ϕ_π and $\phi_{\Delta y_4}$, which makes it difficult to estimate the two parameters simultaneously with any precision. Since the Taylor principle requires $\phi_\pi > 0$ and monetary policy responds to the 1-quarter output growth rate, we set $\phi_{\Delta y_4} = 0$ in the early sample, allowing ϕ_π to be estimated with greater accuracy.

The standard errors of the shock-process innovations are given an inverse-gamma prior distribution with two degrees of freedom—a very loose prior. The mean of the distribution is specific to the shock process. For innovations to the multifactor technology, investment efficiency, preference, and government spending shock processes, the prior distribution of the standard deviation has a mean of 0.01, whereas the prior distributions for the price markup, wage markup, and policy-rate innovations have means of 0.1, 1.0, and 0.002, respectively. As for the innovation to the inflation target, its standard deviation has a prior distribution with a 0.005 mean in the early and middle samples and a 0.002 mean in the late sample.

Moving-average and autoregressive parameters in the various shock processes are given a beta prior distribution with a mean of 0.5 and a standard error of 0.2. The exception (as previously discussed) is that the inflation target is assumed to follow a random walk ($\rho_\pi = 1.0$) in the middle sample.

4.2 Model Comparison

We compare the fit of our different estimated models by using the Laplace Approximation to calculate the marginal density of the data given each model. The Laplace Approximation for model i, $LP(i)$, is a function of that model's posterior distribution, $p(\Theta_i|\mathbf{Y}_T, i)$, as follows:

$$LP(i) = \ln\left((2\pi)^{m_i/2}|\Sigma_{\widehat{\Theta}_i}|^{-1/2} p(\mathbf{Y}_T|\widehat{\Theta}_i, i) p(\widehat{\Theta}_i|i)\right),$$

where m_i is the number of estimated parameters in model i, and $|\Sigma_{\widehat{\Theta}}|$ is the determinant of the $m_i \times m_i$ Hessian matrix of the negative log posterior evaluated at $\widehat{\Theta}_i$. The term $(2\pi)^{m_i/2}|\Sigma_{\widehat{\Theta}_i}|^{-1/2}$ in the above expression is a penalty that is increasing in the number of estimated parameters. Next, the posterior probability of model i is calculated according to:

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

where z is the number of models examined. The greater $\rho(i)$, the greater the likelihood that the data are generated by model i rather than one of the other models under consideration.

Table 3 displays the posterior probabilities for each of our 16 models of nominal frictions in the early, middle, and late samples. Each row of Panels A-C represents a particular form of wage setting while each column denotes a specific type of price setting. A comparison of posterior odds reveals how much more likely it is that the real-world data were generated by a model with one particular combination of price and wage rigidities than another model with an alternative set of nominal frictions. For example, Panel A shows the odds that our early-sample data were generated by a model with dynamic wage adjustment and static price adjustment (0.324) are roughly 3 times greater than a model with static wage and static price adjustment (0.101). In our late sample, however, Panel C reveals that the dynamic-wage/static-price model (0.092) is only 1/5 as likely to have generated the data as the static-wage/static-price model (0.510).

The sum of each column in Panels A-C gives the overall likelihood that sample data were generated by a particular type of price setting. In our early and late samples, static price adjustment with posterior odds equal to 0.772 and 0.974, respectively, dominates alternative models of nominal price setting. That result has intuitive appeal given the abundance of evidence from prior studies suggesting that monetary policy anchored inflation expectations during those periods. In the middle sample, our results suggest that price-setting arrangements incorporated some degree of indexation to past price inflation. In other words, the sum of the posterior odds for the partial-indexation and dynamic-indexation pricing models is almost 80 percent ($0.434 + 0.357 = 0.791$). The fact that price setting exhibited some degree of indexation is consistent with empirical studies that have indicated inflation followed a non-stationary process during the 1970s.

The total of each row denotes the overall likelihood that a specific model of nominal wage setting best describes the sample data. First, we consider the early and late samples, which are both periods in which monetary policy appears to have anchored inflation expectations. A comparison of Panels A and C shows there is a pronounced reduction in the posterior probabilities attached to models in which wages are fully indexed to lagged inflation, and a substantial increase in the probabilities attached to models with static wage indexation. Specifically, the posterior probabilities for the models with dynamic wage indexation fall from 0.474 in the early sample to 0.094 in the late sample, whereas they correspondingly rise from 0.113 to 0.525 for static wage indexation. In contrast, the posterior probabilities for models with partial wage indexation hold relatively steady over time with 0.412 in the early sample and 0.381 in the late sample. The relative similarity of monetary policy in the early and late samples means that the shift in wage setting from dynamic indexation to static indexation was likely due to institutional changes in the labor market and not to monetary policy.[19] Results for the middle sample (Panel B) presumably reflect the combined effects of the changes in the labor market and a monetary policy that lost control of inflation. The middle sample's posterior probabilities for static wage indexation and partial wage indexation are similar to their respective values in the early sample. The main difference between the two samples is that the posterior probabilities for sticky-information wages gain at the expense of dynamic wage indexation. When comparing the middle and late samples, the posterior probabilities for the models with static wage indexation are higher in the late period. This shift is consistent with the notion that future inflation was more variable and uncertain from 1969 to 1979 than it was after 1982.

To summarize, static indexation is the dominant model of nominal price frictions in our early and late sample periods. Given that price-friction model, partial wage indexation best explains the early-sample data, whereas static wage indexation best explains the late-sample data. In our middle sample, partial indexation is the dominant wage-frictions model, and partial price indexation is more consistent with the data than the other alternative approaches. Accordingly, our baseline price and wage frictions models are static price indexation and partial wage indexation in the early sample, partial price indexation and partial wage indexation in the middle sample, and static price indexation and static wage indexation in the late sample.

[19] As noted in Section 1.2, the percentage of union workers covered by automatic COLAs was roughly equal in our early and late samples, but the percentage of the workforce that was unionized fell markedly between those two periods.

4.3 Baseline Parameter Estimates

The baseline model parameter estimates for our three samples are displayed in Table 4A. Each parameter estimate is the mean value of that parameter's posterior distribution which is generated using the Metropolis-Hastings algorithm. To gain insight on the variability of our parameter estimates, we also report the 5th and 95th percentiles for each parameter's posterior distribution. Several aspects of our parameter estimates are worth mentioning. For example, government spending shocks vary considerably more in the middle sample than in either the early or late sample, whereas preference shocks are much more variable in the late sample. Technology and inflation-target shocks, on the other hand, exhibit substantially less variation in the late sample. In addition, technology, investment-efficiency, and wage markup shocks are more persistent in the late sample than in the earlier two samples.

Table 4B displays the unconditional standard deviations for our eight exogenous variables. The unconditional standard deviation of an exogenous variable is influenced by both the variability of the disturbance term and the coefficients on the autoregressive and moving average terms in the shock process. In a number of instances, changes in the standard deviation of the disturbance term and the coefficients in the shock process offset each other so that the unconditional standard deviation of the variable remains relatively constant. For example, government spending innovations are more variable in the middle sample than in the late sample, but those shocks are also less persistent. Those changes almost completely offset each other so that the unconditional standard deviation of government spending across the two samples is nearly identical. Similarly, technology innovations are much less variable but more persistent in the late sample than in the early sample such that the unconditional standard deviation of technology is only slightly larger in the late sample. The unconditional standard deviations for the other exogenous variables vary substantially across periods. For instance, the unconditional standard deviation of the price markup parameter, $\theta_{p,t}$, is *twice* as large in the late sample as in either earlier sample, whereas the unconditional standard deviation of the wage markup parameter, $\theta_{w,t}$, is *half* as large in the late sample as in the early sample.

The estimates for the inflation-target and policy-rate shock processes provide a glimpse into the conduct of monetary policy during our three samples. Table 4A shows that inflation-target shocks are equally persistent in the early and late samples, $\rho_\pi = 0.74$ and $\rho_\pi = 0.78$, respectively, but follow a unit-root process in the middle sample (*c.f.* footnote #17). The standard deviation of the inflation target shock, however, declines by about 1/3 from the early sample to the middle sample and by another 1/3 as one moves to the late sample. Those estimates imply that longer-run inflation expectations went from being loosely anchored (early sample), to unanchored (middle sample), to well anchored (late sample). To illustrate inflation's behavior, Figure 3 compares the actual annualized quarterly inflation rate (blue dashed line) with the implied inflation rate target (red solid line) which is derived from the estimated shocks to the inflation target process. The poor conduct of monetary policy during the 1970s is also reinforced by the much larger standard deviation of the policy-rate shock in the middle sample, 0.0028, than in either the early or late sample, 0.0009 and 0.0008, respectively. In other words, monetary policy more tightly related short-term interest rates to output growth and inflation in the early and late samples than in the middle sample.

Our estimates also reveal that the frequency of price and wage re-optimizations change over time. Table 4A shows the frequency of price re-optimization, η_p, increased by about 1/3 between the early and middle samples, and then fell by over 1/2 in the late sample. In contrast, the frequency of wage re-optimization, η_w, was relatively stable between the early and middle samples and then increased by 38 percent in the late sample. The higher estimated rate of price re-optimization during the middle sample plausibly reflects the unanchored and uncertain monetary policy of that period, as compared to the early and, especially, the late samples. The more frequent re-optimization of wages over time likely signifies the shrinking importance of unions and their multi-year labor contracts as shown in Figure 1.

5 Empirical Implications

5.1 Variance Decompositions

Table 5 shows variance decompositions for output, the inflation rate, and the short-term nominal interest rate over our three samples. Panels A and B report the conditional variance decompositions of each variable at forecast horizons of 1 and 4 quarters, respectively, while Panel C displays their unconditional variance decompositions. The middle-sample decompositions for inflation and the interest rate are not comparable to their respective early- and late-sample decompositions because both variables in the middle sample are measured relative to the non-stationary stochastic trend in the inflation rate target. The variance decompositions for output, in contrast, are not influenced by the inflation target, so their values are comparable across all three samples.

The forecast error variance decompositions reveal that the underlying sources of output variation have changed over time. Beginning with the 4-quarter forecast horizon, we examine how the impact of the exogenous shocks on output changes over our sample periods. Multifactor technology shocks account for less of output's variability over time while shocks to the marginal efficiency of investment increase. Specifically, output movements caused by multifactor technology shocks decline from 34 percent in the early sample to 22 percent and 7 percent in the middle and late samples, respectively, whereas the investment efficiency shocks rise from 5 percent in the early sample to 31 and 34 percent in the middle and late samples, respectively. The combined contributions of both technology shocks to output's variability is about 40 percent in the early and late samples but over 50 percent in the middle sample. Individually, the impact of preference and government spending shocks on output variability has risen from 1 percent in the early sample to 6 percent in the late sample. Price and wage markup shocks' influence on output movements has moved in the opposite directions over time with price markup shocks having a smaller influence as time progress, while wage markup shocks have a larger effect. The combined contribution of the two markup shocks to output variability is between 38 and 42 percent in the early and late samples, respectively, but dips to 29 percent in the middle sample. Lastly, the impact of monetary policy on output volatility has declined substantially over our sample periods. The inflation target and policy rate shocks together are responsible for 21 percent of output movements in the early sample but that amount drops to 8 percent and 4 percent in the middle and late samples, respectively. In general, monetary policy shocks account for a smaller fraction of output movements over time, while other shocks, such as government spending and preferences, make up larger percentages. At the forecast horizons of 1-quarter and infinity, the variance decompositions for output display similar behavior over time to the patterns observed at the 4-quarter horizon.

The variance decompositions reveal that there are pronounced changes in the sources of inflation variation between the early and late samples. Beginning with the 4-quarter forecast horizon, inflation-target shocks explain an overwhelming share of inflation's movements in the early sample, while price and wage markup shocks account for most of inflation's variability in the late sample. Inflation target shocks explain 67 percent of inflation fluctuations in the early sample but only 12 percent in the late sample. In contrast, price and wage markup shocks account for a total of 76 percent of inflation's variability in the late sample, but only 18 percent in the early sample. Results at the infinite horizon are qualitatively and quantitatively similar. At the 1-quarter forecast horizon, the effects observed at the 4-quarter horizon remain, but there are additional noticeable declines in the relative importance of multifactor technology and investment efficiency shocks between the early and late samples. Specifically, the combined contribution of those two shocks to inflation variability falls from 20 percent to 6 percent.

The variance decompositions for the nominal interest rate, like inflation, are comparable between the early and late samples but not the middle sample. At the 4-quarter forecast horizon, both technology shocks consistently account for between 32 and 35 percent of interest rate variations in the early and late samples, whereas government spending shocks remain between 3 and 4 percent. The preference, markup, and monetary policy shocks, in contrast, have different effects on interest rate movements in the early and late samples. Specifically, the relative importance of preference shocks doubles from the early to late samples, whereas the combined share of price and wage markup shocks increases ten fold. Interest rate movements arising from inflation-target and policy-rate shocks, in contrast, decline substantially from the early to late samples. Qualitatively similar changes in the variance decompositions are observed at the infinite forecast horizon, except that multifactor technology shocks decline in importance over time relative to investment-efficiency shocks. The nominal interest rate's variance decomposition is much different at the 1-quarter forecast horizon. Most importantly, policy rate shocks are the primary driver of interest rate movements in all three samples. That result means that policy implementation errors, which are the main source of policy shocks, are the leading factors causing the nominal interest rate to move in the extreme short run. As for the other sources of variation, both technology shocks account for more interest rate fluctuations in the early sample than in the late sample, whereas price markup shocks are responsible for a larger share in the late sample. The preference, government spending, and wage markup shocks, on the other hand, all have roughly the same effect on the nominal interest rate in the early and late samples.

In summary, monetary policy shocks are responsible for a larger fraction of output fluctuations in the early sample than in the later samples while other shocks, such as government spending and preferences, explain a greater share in the late sample. Inflation movements are driven by inflation target shocks in the early sample and price and wage markup shocks in the late sample. As for the nominal interest rate, its variability is propelled mainly by monetary policy shocks in the early sample while markup shocks account for a greater percentage in the late sample.

5.2 Decomposition of Historical Output Fluctuations: The Great Moderation

Historical fluctuations in output, inflation, the interest rate and other endogenous variables can be attributed to current and lagged realizations of various exogenous shocks. The decomposition of historical output movements across our different samples sheds light on some possible causes of the Great Moderation in real activity that begins around 1984 (McConnell and Perez-Quiros, 2000). The last row of Table 6 documents the decline in output volatility during the late sample. Specifically, the standard deviation of (de-trended log) output is close to 2.4 percentage points in the early and middle samples but falls by 1/3 to 1.6 percentage points in the late sample. The source of the decline depends on whether one is comparing the early and late samples or the middle and late samples.

A comparison of the early sample and late sample historical decompositions of output reveals that all of the reduction in output volatility between the two periods can be attributed to monetary policy. Specifically, inflation target shocks raised the standard deviation of output by a full percentage point in the early sample, but lowered the standard deviation of output by 0.3 percentage points in the late sample. In contrast, technology, preference, and markup shocks made modestly larger contributions to output fluctuations in the late sample than in the early sample.

The main source of reduced output volatility from the middle to late sample is a sizable decline in the contribution from multifactor technology shocks. That is, multifactor technology shocks raised the standard deviation of output by more than 1 percentage point in the middle sample, but then lowered the standard deviation of output by 0.2 percentage points in the late sample. Most of the other exogenous shocks either helped moderate the decline in output volatility from the middle to late sample or had no meaningful effect. Specifically, preference, investment efficiency, and wage markup shocks had a larger effect on output volatility in the late sample, whereas government spending, price markup, and policy rate shocks had basically the same effect.

5.3 Impulse Response Functions

Figures 4A-B display the Bayesian impulse response functions for output, inflation, and the nominal interest rate to each of the eight exogenous shocks. Each impulse response function is calculated as the mean of a distribution of impulse responses to a one standard deviation shock when the parameters are drawn from the posterior distribution. Our early-sample impulse responses are shown in black (solid line) along with their 90 percent confidence bands. The middle-sample and late-sample impulse responses are plotted in red (dashed line) and blue (dash-dotted line), respectively, without confidence bands.

The left column of Figures 4A-B shows that output responds as expected to each shock. Positive shocks to preferences, multifactor technology, investment efficiency, government spending, and the inflation target all cause near-term output to increase.[20] In contrast,

[20] A preference shock is slightly different from a discount-factor shock. A positive preference shock indicates the households are placing more value on current consumption, whereas a positive discount-factor shock indicates households are placing more value on future consumption. Therefore, a positive preference shock resembles a negative discount-factor shock.

output immediately declines in response to positive shocks to the price markup, the wage markup, and the policy rate.[21] Most of our model's exogenous shocks generate a "hump-shaped" response in output, but there are some exceptions. A rise in government spending's share of output has an immediate expansionary impact, which gradually decays. In the early and middle samples, positive preference and investment efficiency shocks push output to its peak on impact, whereas both shocks raise output in a hump-shaped manner in the late sample. In general, output's impulse responses are initially weaker and peak later in the late sample than in the earlier samples. Late-sample shocks to multifactor technology, the price markup, the inflation target, and the policy rate also produce a much smaller change in output than in the early sample. That weaker output response extends to the middle sample for the policy rate shock. The smoother and in some cases weaker output responses observed in the late sample are consistent with the reduced high-frequency output variation that defines the Great Moderation. In fact, the wage markup shock is the only exogenous disturbance that generates a much stronger output response in the late sample than in the earlier samples.

The response of inflation to each of the exogenous shocks is displayed in the middle column of Figures 4A-B. As expected, positive shocks to preferences, government spending, investment efficiency, the price markup, the wage markup, and the inflation target push up inflation, whereas increases in multifactor technology and the policy rate reduce inflation. Our analysis of inflation's response to an inflation target shock is complicated by the fact that the inflation target follows a random walk during the middle sample so that all inflation target shocks in that period are permanent. To maintain stationarity in the middle sample, inflation's response to an exogenous shock is measured as inflation's deviation from the inflation target. For example, an impulse response of zero for inflation indicates that inflation is equal to its target. That difference means that inflation's response to an inflation target shock in the middle sample is not directly comparable to its responses in the early or late samples. A permanent increase in the middle sample's inflation target causes inflation to increase immediately but by a smaller amount than the inflation target, which explains why inflation's response in Figure 4B is initially negative. In subsequent periods, inflation rises above its target only to eventually fall back to that same level. In the early and late samples, however, a positive inflation target shock causes inflation to jump immediately to its peak, and then to gradually fall back to its steady state.

Inflation's middle-sample responses to non-monetary shocks are similar in form to its responses in the early sample. Positive shocks to preferences, government spending, and investment efficiency raise inflation immediately. Inflation then gradually declines toward its steady state in subsequent periods. In another case, inflation initially declines following a positive multifactor technology shock and then gradually rises for several periods. That increase is sustained enough to cause inflation to temporarily rise above its steady state before returning to its long-run level. Positive price and wage markup shocks during the early and middle samples also produce that same overshooting response in inflation except in reverse. In the late sample, all of inflation's impulse responses peak on impact and then monotonically return to steady state without overshooting. The impulse responses

[21] In our framework, $\varepsilon_{w,t} < 0$ and $\varepsilon_{p,t} < 0$ signify a positive wage markup shock and a positive price markup shock, respectively. See Sections 2.1 and 2.2 for more details.

for inflation are not consistently larger or smaller in any one particular sample. Another interesting result is that inflation's response to multifactor technology shocks is much larger in the middle sample than in the late sample. That result is consistent with the belief that the FOMC routinely accommodated commodity price increases (a negative multifactor technology shock) during the 1970s, but rarely, if ever, did so during the Great Moderation.[22]

Comparison of the early- and middle-sample impulse responses for the nominal interest rate reveals that both exhibit a similar pattern with the middle-sample responses being more amplified.[23] Those larger responses even occur when the behavior of output and inflation is quite similar across the two samples. For example, preference, government spending, and investment efficiency shocks generate similar inflation and output dynamics in the early and middle samples, while the interest rate response is much bigger in the middle sample. Two factors driving the middle-sample's interest rate dynamics are the somewhat stronger response of monetary policy to inflation and output growth and the greater emphasis on interest rate smoothing in the policy rule (*i.e.*, $\phi_{R_1} + \phi_{R_2}$ is larger). Lastly, the especially large standard deviation of ε_R in the middle sample contributes to the greater interest rate response to a policy rate shock during that period.

The late-sample non-monetary policy shocks generate larger and more strongly hump-shaped interest rate responses than in the early sample. Those higher interest rate responses are produced, in part, by monetary policy's more aggressive response to inflation and output growth in the late sample. The longer time between the initial shock and the subsequent peak in the interest rate response is caused in part by the tendency for output responses to be hump-shaped in the late sample.

6 Summary and Suggestions for Future Research

Our results indicate that many popular models of nominal frictions are not robust. None of our 16 models of nominal price and wage frictions performs consistently well across the range of changes in unionization and the conduct of monetary policy the U.S. has experienced in the post-World-War-II era. The data suggest that a sticky price and sticky wage model with static price indexation and partial wage indexation best explains the U.S. economy in our early sample (1955:Q1-1968:Q4) when unionization was high and monetary policy loosely anchored inflation. The middle-sample (1969:Q1-1979:Q3) data indicate that a model with partial indexation of both prices and wages best accounts for the U.S. economy during a period with moderately high rates of unionization and a monetary policy that failed to anchor inflation. Finally, our results show that the late-sample (1983:Q1-2007:Q4) behavior of the U.S. economy is best represented by a sticky price and sticky wage model with static

[22] "I find that oil shocks contributed substantially to core inflation until 1981, but since that time pass-through has been largely absent. The evidence for this regime-break result is highly significant and robust..." (Hooker, 2002). Gavin, Keen, and Kydland (forthcoming) build a model with an energy sector and a tax code to theoretically explain the mechanism by which the FOMC could accommodate energy price shocks in the 1970s with higher inflation but then discontinue that accommodation starting in the early 1980s.

[23] An exception to the "similar pattern" characterization is the interest rate response to an inflation target shock. Since inflation target shocks are permanent in the middle sample, the impulse response function shows the Fed sharply cutting its nominal interest rate target in order to push inflation up toward its new higher target.

price and wage indexation during a time characterized by low unionization rates and a monetary policy with a strong inflation anchor. Those results highlight the likelihood that popular models of price and wage adjustment are unable to endogenously respond to realistic institutional and policy changes. Therefore, macroeconomic analyses based on such models should be considered as valid approximations only in a quite limited range of institutional and policy environments.

Three additional findings from this paper are important and worth reiterating. First, estimates of the frequency of price and wage re-optimization indicate that prices have become stickier in the later samples while wages have become less sticky. Second, comparison of the volatility of output over the three samples reveals that smaller technology shocks and improved monetary policy both contributed to the Great Moderation in output volatility that began in the early 1980s. Third, inflation was much less sensitive to multifactor technology shocks in the late sample than in the middle sample—a result that is consistent with the general view that the FOMC was more willing to accommodate commodity price increases in the 1970s than in subsequent decades.

Future research could proceed in a couple of 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. Specifically, one needs to carefully model the endogeneity of nominal frictions to determine the circumstances in which one pricing specification is likely to be preferred to the alternatives. In that vein, Cogley and Sbordone (2008) show that if the permanent component of inflation is identifiable, then price re-optimizing firms will systematically place greater weight on future economic conditions as trend inflation rises. Consequently, Phillips-curve coefficients vary endogenously with trend inflation.[24] Once those shifting weights are taken into account, Cogley and Sbordone (2008) find no evidence of dynamic indexation in the data: Firms appear to hold their prices constant between re-optimizations.

The second approach for future research is to develop a model of nominal frictions that is flexible enough to perform well over a wide range of time periods and policy regimes. 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. Ireland's empirical results indicate that firms completely index to the inflation rate target and place zero weight on lagged inflation.[25] Those results are consistent with the conclusion reached here, that the sophistication of firms' pricing is not adequately captured by the standard sticky price and sticky information models.

[24] Coibion and Gorodnichenko (2011a) examine the interaction between trend inflation, the degree in which price re-optimization is forward looking, and the possible indeterminacy of monetary policy.

[25] Along the lines of Ireland (2007), Davig and Doh (2014) specify a price rule which enables an endogenous response to shifts in monetary policy. They assume that prices are indexed to trend inflation between re-optimizations, 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] 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.

[2] Ball, Laurence, N. Gregory Mankiw, and David Romer (1988) "The New Keynesian Economics and the Output-Inflation Trade-off," *Brookings Papers on Economic Activity*, 1, 1-65.

[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 Jordi Gali (2009) "The Macroeconomic Effects of Oil Price Shocks: Why are the 2000s so different from the 1970s?" In *International Dimensions of Monetary Policy*, ed. Jordi Gali and Mark J. Gertler, 373-421, Chicago, IL: University of Chicago Press.

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

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

[7] Chari, V.V., Patrick J. Kehoe, and Ellen R. McGrattan (2000) "Sticky Price Models of the Business Cycle: Can the Contract Multiplier Solve the Persistence Problem," *Econometrica*, 68(5), 1151-1179.

[8] 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.

[9] Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno (2010) "Financial Factors in Business Cycles," ECB Working Paper No. 1192.

[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] 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.

[12] 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.

[13] Coibion, Olivier (2010) "Testing the Sticky Information Phillips Curve," *Review of Economics and Statistics*, 92(1), 87-101.

[14] Coibion, Olivier and Yuriy Gorodnichenko (2011a) "Monetary Policy, Trend Inflation and the Great Moderation: An Alternative Interpretation," *American Economic Review*, 101(1), 341-370.

[15] Coibion, Olivier and Yuriy Gorodnichenko (2011b) "Strategic Interaction Among Heterogenous Price-Setters in an Estimated DSGE model," *Review of Economics and Statistics*, 93(3), 920-940.

[16] Davig, Troy and Taeyoung Doh (2014) "Monetary Policy Regime Shifts and Inflation Persistence," *Review of Economics and Statistics*, 26(5), 862-875.

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

[18] Devine, Janice M. (1996) "Cost-of-living Clauses: Trends and Current Characteristics," Compensation and Working Conditions (December), 24-29.

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

[20] Dupor, Bill, Tomiyuki Kitamura, and Takayuki Tsuruga (2010) "Integrating Sticky Prices and Sticky Information," *Review of Economics and Statistics*, 92(3), 657-669.

[21] Edge, Rochelle (2002) "The Equivalence of Wage and Price Staggering in Monetary Business Cycle Models," *Review of Economic Dynamics*, 5(3), 559-585.

[22] 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.

[23] 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.

[24] 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.

[25] Gavin, William T., Benjamin D. Keen, and Finn E. Kydland (forthcoming) "Monetary Policy, the Tax Code, and the Real Effects of Energy Shocks," *Review of Economic Dynamics*.

[26] Greenwood, Jeremy, Zvi Hercowitz, and Gregory W. Huffman (1988) "Investment, Capacity Utilization, and the Real Business Cycle," *American Economic Review*, 78(3), 402-417.

[27] Hirsch, Barry (2008) "Sluggish Institutions in a Dynamic World: Can Unions and Industrial Competition Coexist?" *Journal of Economic Perspectives*, 22(1), 153-176.

[28] Hooker, Mark A. (2002) "Are Oil Shocks Inflationary? Asymmetric and Nonlinear Specifications versus Changes in Regime," *Journal of Money, Credit, and Banking*, 34(2), 540-561.

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

[30] 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.

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

[32] 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.

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

[34] 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.

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

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

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

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

[39] Kozicki, Sharon, and P.A. Tinsley (2009) "Perhaps the 1970s FOMC Did What It Said It Did," *Journal of Monetary Economics*, 55(6), 842-855.

[40] 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.

[41] Levin, Andrew T. and Jeremy M. Piger (2008), "Bayesian Model Selection for Structural Break Models," Manuscript, University of Oregon.

[42] 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.

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

[44] 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.

[45] 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.

[46] Murray, Christian, Alex Nikolsko-Rzhevskyy, and David Papell (2015) "Markov Switching and the Taylor Principle," *Macroeconomic Dynamics*, 19(4).

[47] Nikolsko-Rzhevskyy, Alex and David Papell (2012) "Taylor Rules and the Great Inflation," *Journal of Macroeconomics*, 34(4), 903-918.

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

[49] Rabanal, Pau and Juan F. Rubio-Ramirez (2005) "Comparing New Keynesian Models of the Business Cycle: A Bayesian Approach," *Journal of Monetary Economics*, 52(6), 1151-1166.

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

[51] 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.

[52] Smets, Frank and Rafael Wouters (2007) "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, 97(3), 586-606.

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

[54] Weiner, Stuart E. (1986) "Union COLA's on the Decline," Federal Reserve Bank of Kansas City Economic Review (June), 10-25.

Table 1: Nominal Frictions in Estimated Dynamic Macro Models

DSGE models	Sample(s)	Nominal frictions	Indexation
Ireland (2001)	1959:Q1-1979:Q2 1979:Q3-1998:Q4	Price	Static, Dynamic
Andre, Lopez-Salido, Nelson (2005)	1979:Q3-2003:Q3	Price	Static, Dynamic, Sticky Info.
Rabanal, Rubio-Ramirez (2005)	1960:Q1-2001:Q4 1982:Q4-2001:Q4	Price, Wage	Static, Dynamic
Laforte (2007)	1983:Q1-2003:Q1	Price	Static, Dynamic, Sticky Info.
Coibion, Gorodnichenko (2011b)	1982:Q1-2008:Q2	Price	Static, Dynamic, Sticky Info.
Keen, Koenig (–)	1955:Q1-1968:Q4 1969:Q1-1979:Q3 1983:Q1-2007:Q4	Price, Wage	Static, Dynamic, Sticky Info.

Partial equilibrium models	Sample(s)	Nominal frictions	Indexation
Kiley (2007)	1965:Q1-2002:Q4 1983:Q1-2002:Q4	Price	Static, Dynamic, Sticky Info.
Korenok (2008)	1960:Q1-2002:Q1 1983:Q1-2002:Q1	Price	Static, Sticky Info.
Coibion (2010)	1971:Q2-2004:Q2 1984:Q1-2004:Q2	Price	Static, Sticky Info.
Dupor, Kitamura, Tsuruga (2010)	1960:Q1-2007:Q2 1960:Q1-1979:Q2 1984:Q1-2007:Q2	Price	Static, Dynamic, Sticky Info.

Table 2: Prior Distributions for Structural Parameters[†]

	Prior Distribution		Prior Distribution
Technology & Preferences		Shock Processes	
α	Normal(0.3,0.05)	ρ_Z	Beta(0.5,0.2)
κ	Normal(4,1.5)	ρ_J	Beta(0.5,0.2)
b	Beta(0.7,0.15)	ρ_G	Beta(0.5,0.2)
$\frac{1}{(\zeta+1)}$	Beta(0.75,0.15)	ρ_a	Beta(0.5,0.2)
Price & Wage		ρ_p	Beta(0.5,0.2)
η_p	Beta(0.25,0.1)	ρ_w	Beta(0.5,0.2)
η_w	Beta(0.25,0.1)	ρ_π	Beta(0.5,0.2)
γ_p	Beta(0.5,0.2)	μ_p	Beta(0.5,0.2)
γ_w	Beta(0.5,0.2)	μ_w	Beta(0.5,0.2)
Taylor Rule		σ_Z	Inv-Gamma(0.01,2)
ϕ_{R_1}	Uniform(-2,2)	σ_J	Inv-Gamma(0.01,2)
ϕ_{R_2}	Uniform(-2,2)	σ_G	Inv-Gamma(0.01,2)
ϕ_π	Uniform(0,2)	σ_a	Inv-Gamma(0.01,2)
$\phi_{\Delta y_1}$	Uniform(-1,1)	σ_p	Inv-Gamma(0.1,2)
$\phi_{\Delta y_4}$	Uniform(-1,1)	σ_w	Inv-Gamma(1,2)
		σ_π	Inv-Gamma(0.005,2)[‡]
		σ_R	Inv-Gamma(0.002,2)

† The numbers in parentheses denote the mean and standard deviation for the Normal and Beta distributions, the lower and upper bounds for the Uniform distribution, and the mean and degrees of freedom for the Inverse-Gamma distribution.

‡ Prior distribution for the late sample is Inv-Gamma(0.002,2).

Table 3: Model Comparison: Posterior Odds

Panel A: Early Sample (1955:Q1-1968:Q4)

Wage\Price	Static	Partial	Dynamic	Sticky Info.	Total
Static	0.101	0.003	0.000	0.009	0.113
Partial	0.346	0.009	0.000	0.057	0.412
Dynamic	0.324	0.007	0.000	0.143	0.474
Sticky Info.	0.001	0.000	0.000	0.000	0.001
Total	0.772	0.019	0.000	0.209	1.000

Panel B: Middle Sample (1969:Q1-1979:Q3)

Wage\Price	Static	Partial	Dynamic	Sticky Info.	Total
Static	0.025	0.046	0.031	0.001	0.103
Partial	0.085	0.198	0.160	0.013	0.456
Dynamic	0.036	0.069	0.046	0.014	0.165
Sticky Info.	0.032	0.121	0.120	0.003	0.276
Total	0.178	0.434	0.357	0.031	1.000

Panel C: Late Sample (1983:Q1-2007:Q4)

Wage\Price	Static	Partial	Dynamic	Sticky Info.	Total
Static	0.510	0.014	0.000	0.001	0.525
Partial	0.372	0.008	0.000	0.001	0.381
Dynamic	0.092	0.002	0.000	0.000	0.094
Sticky Info.	0.000	0.000	0.000	0.000	0.000
Total	0.974	0.024	0.000	0.002	1.000

Table 4A: Comparison of Baseline Parameter Estimates (Metropolis-Hastings)

	1955:Q1-1968:Q4			1969:Q1-1979:Q3			1983:Q1-2007:Q4		
	5%	Mean	95%	5%	Mean	95%	5%	Mean	95%
Technology & Preferences									
α	0.2357	0.2620	0.2882	0.2177	0.2529	0.2903	0.1981	0.2249	0.2511
κ	0.1294	0.4247	0.7591	0.2844	1.4332	2.6133	3.2979	5.1882	7.0589
b	0.6018	0.7179	0.8390	0.6100	0.7056	0.8007	0.7856	0.8451	0.9090
$\frac{1}{(\zeta+1)}$	0.6541	0.8063	0.9698	0.6526	0.8148	0.9854	0.5570	0.7489	0.9570
Price & Wage									
η_p	0.1922	0.2419	0.2927	0.2430	0.3237	0.4028	0.1076	0.1507	0.1914
η_w	0.1684	0.2477	0.3265	0.1602	0.2698	0.3729	0.2087	0.3378	0.4664
γ_p	–	$\equiv 0$	–	0.1711	0.4871	0.7965	–	$\equiv 0$	–
γ_w	0.2387	0.5307	0.8442	0.2167	0.5038	0.7984	–	$\equiv 0$	–
Taylor Rule									
ϕ_{R_1}	1.2655	1.5412	1.8467	0.8197	1.1261	1.4306	0.7507	1.0010	1.2386
ϕ_{R_2}	−1.0793	−0.8043	−0.5209	−0.6281	−0.2825	0.0801	−0.4481	−0.2638	−0.0726
ϕ_π	0.0769	0.4931	0.9590	0.1016	0.5927	1.0668	0.3783	0.6857	0.9919
$\phi_{\Delta y_1}$	0.0427	0.0733	0.1024	−0.0843	0.0306	0.1364	−0.0090	0.0329	0.0744
$\phi_{\Delta y_4}$	–	$\equiv 0$	–	0.1319	0.3781	0.6156	0.0890	0.2080	0.3207
Shock Processes									
ρ_Z	0.8074	0.8665	0.9280	0.6687	0.7837	0.9061	0.9481	0.9683	0.9896
ρ_J	0.1057	0.3714	0.6333	0.0760	0.2793	0.4681	0.6166	0.7264	0.8425
ρ_G	0.6561	0.7808	0.9131	0.6817	0.8035	0.9375	0.8965	0.9364	0.9772
ρ_a	0.1096	0.3363	0.5632	0.2391	0.4559	0.6772	0.2811	0.4902	0.7043
ρ_p	0.8819	0.9343	0.9872	0.3631	0.6010	0.8515	0.8254	0.8850	0.9453
ρ_w	0.1345	0.3916	0.6466	0.2193	0.4857	0.7479	0.8321	0.9077	0.9816
ρ_π	0.6067	0.7366	0.8713	–	$\equiv 1$	–	0.6365	0.7842	0.9406
μ_p	0.3288	0.5425	0.7569	0.1358	0.4109	0.6678	0.3810	0.5771	0.7711
μ_w	0.3094	0.5548	0.8609	0.1443	0.4756	0.7674	0.5994	0.7347	0.8821
σ_Z	0.0067	0.0080	0.0092	0.0062	0.0076	0.0089	0.0042	0.0047	0.0053
σ_J	0.0030	0.0130	0.0243	0.0146	0.0585	0.1013	0.0353	0.0563	0.0774
σ_G	0.0032	0.0038	0.0044	0.0039	0.0047	0.0055	0.0025	0.0028	0.0031
σ_a	0.0104	0.0176	0.0247	0.0077	0.0133	0.0188	0.0139	0.0216	0.0293
σ_p	0.0544	0.0954	0.1317	0.0598	0.1279	0.1978	0.1056	0.2338	0.3608
σ_w	0.4362	1.3349	2.3080	0.2658	0.9155	1.1715	0.2463	0.6156	1.0368
σ_π	0.0016	0.0029	0.0042	0.0011	0.0019	0.0027	0.0007	0.0013	0.0020
σ_R	0.0007	0.0009	0.0011	0.0021	0.0028	0.0034	0.0007	0.0008	0.0010

Table 4B: Comparison of Baseline Parameter Estimates (Metropolis-Hastings)

	1955:Q1-1968:Q4			1969:Q1-1979:Q3			1983:Q1-2007:Q4		
	5%	Mean	95%	5%	Mean	95%	5%	Mean	95%
Unconditional Standard Deviations†									
Σ_Z	–	0.0159	–	–	0.0122	–	–	0.0190	–
Σ_J	–	0.0140	–	–	0.0609	–	–	0.0820	–
Σ_G	–	0.0060	–	–	0.0079	–	–	0.0080	–
Σ_a	–	0.0187	–	–	0.0149	–	–	0.0247	–
Σ_p	–	0.1415	–	–	0.1315	–	–	0.2803	–
Σ_w	–	1.3558	–	–	0.9156	–	–	0.6659	–
Σ_π	–	0.0043	–	–	$\equiv \infty$	–	–	0.0022	–
Σ_R	–	0.0009	–	–	0.0028	–	–	0.0008	–

† $\Sigma = \sigma[(1+\mu^2-2\rho\mu)/(1-\rho^2)]^{1/2}$.

Table 5: Forecast Error Variance Decompositions

Panel A: $H = 1$

Shock Process	Output 55-68	Output 69-79	Output 83-07	Inflation Rate 55-68	Inflation Rate 69-79	Inflation Rate 83-07	Interest Rate 55-68	Interest Rate 69-79	Interest Rate 83-07
Multifactor Tech.	19.17	5.66	3.20	17.83	23.66	5.24	2.94	0.03	0.16
Invest. Efficiency	19.15	51.84	32.49	2.39	0.91	1.00	19.17	7.52	10.36
Gov't Spending	7.47	19.74	22.17	0.46	0.33	0.10	6.76	2.86	5.66
Preference	4.95	6.05	16.83	1.24	0.66	1.69	5.65	1.08	6.92
Price Markup	23.50	6.68	12.75	29.49	59.54	72.85	2.40	0.48	8.68
Wage Markup	2.09	3.11	9.97	4.14	12.57	13.41	0.07	0.01	0.25
Inflation Target	19.06	0.43	2.42	43.64	0.10	5.65	8.19	4.32	0.14
Policy Rate	4.61	6.60	0.18	0.81	2.22	0.06	54.82	83.70	67.83

Panel B: $H = 4$

Shock Process	Output 55-68	Output 69-79	Output 83-07	Inflation Rate 55-68	Inflation Rate 69-79	Inflation Rate 83-07	Interest Rate 55-68	Interest Rate 69-79	Interest Rate 83-07
Multifactor Tech.	34.02	22.28	6.66	10.66	28.37	6.68	2.09	1.48	1.62
Invest. Efficiency	5.30	31.10	33.99	2.12	0.98	2.14	30.32	30.96	32.93
Gov't Spending	1.18	6.92	5.77	0.36	0.43	0.16	4.93	7.12	4.85
Preference	0.82	2.79	7.61	1.00	1.18	2.64	7.27	5.20	15.05
Price Markup	35.09	16.13	21.68	15.77	46.83	55.88	1.93	4.30	27.40
Wage Markup	2.75	12.81	20.75	2.29	15.53	20.06	0.44	0.74	4.30
Inflation Target	18.65	0.59	3.42	67.17	0.25	12.35	14.88	2.21	1.05
Policy Rate	2.18	7.38	0.12	0.63	6.43	0.10	38.14	47.99	12.78

Panel C: $H = \infty$

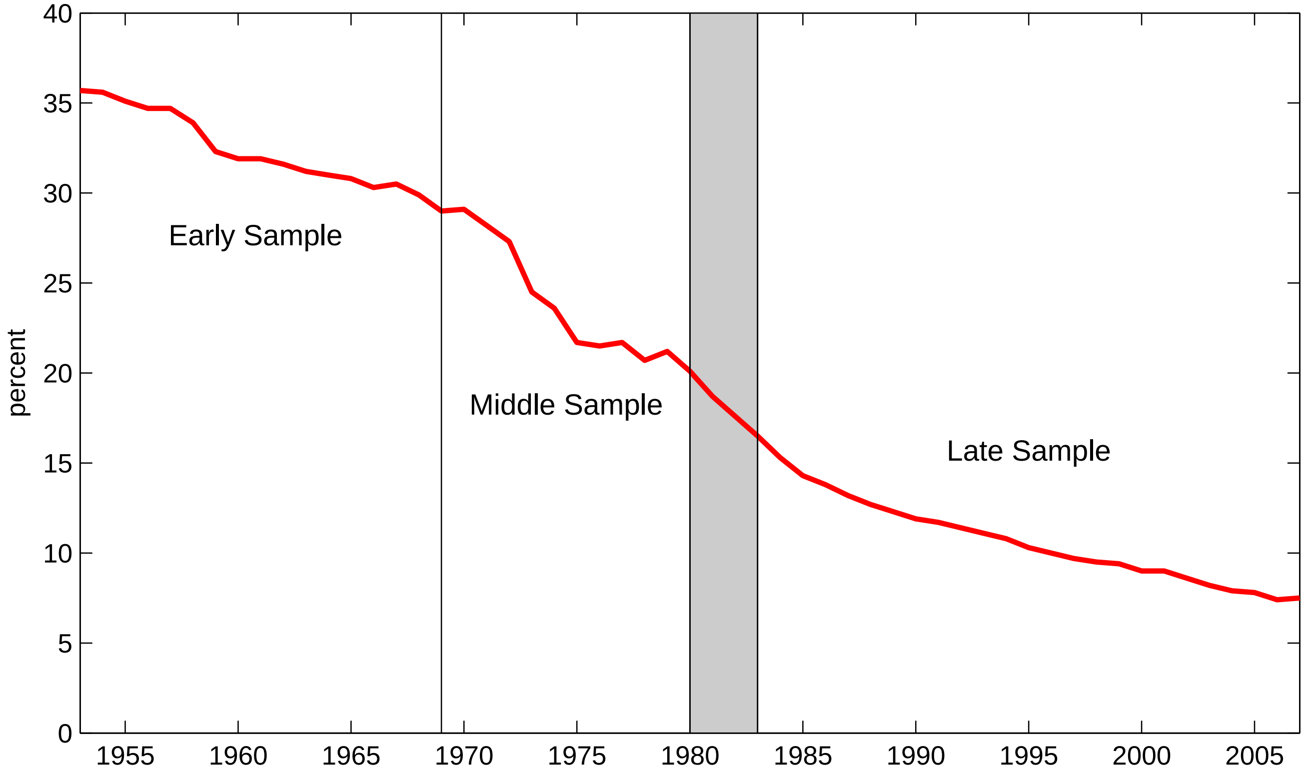
Shock Process	Output 55-68	Output 69-79	Output 83-07	Inflation Rate 55-68	Inflation Rate 69-79	Inflation Rate 83-07	Interest Rate 55-68	Interest Rate 69-79	Interest Rate 83-07
Multifactor Tech.	35.35	30.87	24.01	10.10	29.69	6.28	10.24	3.10	2.55
Invest. Efficiency	2.50	24.32	16.38	2.05	1.35	4.24	26.14	34.15	42.50
Gov't Spending	0.47	4.15	1.46	0.35	0.45	0.33	3.63	6.87	3.03
Preference	0.36	1.66	1.31	0.89	1.01	2.72	6.20	5.77	12.36
Price Markup	45.90	13.27	18.82	14.82	45.31	49.74	10.73	5.32	22.78
Wage Markup	1.73	20.25	36.22	2.00	15.97	19.94	1.35	1.63	9.95
Inflation Target	12.80	0.45	1.79	69.15	0.28	16.64	15.75	1.90	1.01
Policy Rate	0.87	5.04	0.02	0.64	5.94	0.10	25.96	41.24	5.82

Table 6: Contributions of Exogenous Shocks to the Volatility of Output†

Shock Process	Early sample 1955-1968	Middle sample 1969-1979	Late sample 1983-2007
Initial Values	**0.239**	**0.015**	**−0.075**
Technology & Gov't			
Multifactor Tech.	0.086	1.035	−0.202
Invest. Efficiency	0.219	0.488	0.786
Gov't Spending	0.101	−0.005	−0.083
Subtotal	**0.406**	**1.518**	**0.501**
Preference	**0.061**	**0.114**	**0.443**
Markup			
Price Markup	0.265	0.568	0.552
Wage Markup	0.466	0.283	0.511
Subtotal	**0.731**	**0.851**	**1.063**
Monetary Policy			
Inflation Target	1.047	0.038	−0.322
Policy Rate	−0.096	−0.166	−0.017
Subtotal	**0.951**	**−0.128**	**−0.339**
Total Volatility‡	**2.388**	**2.370**	**1.593**

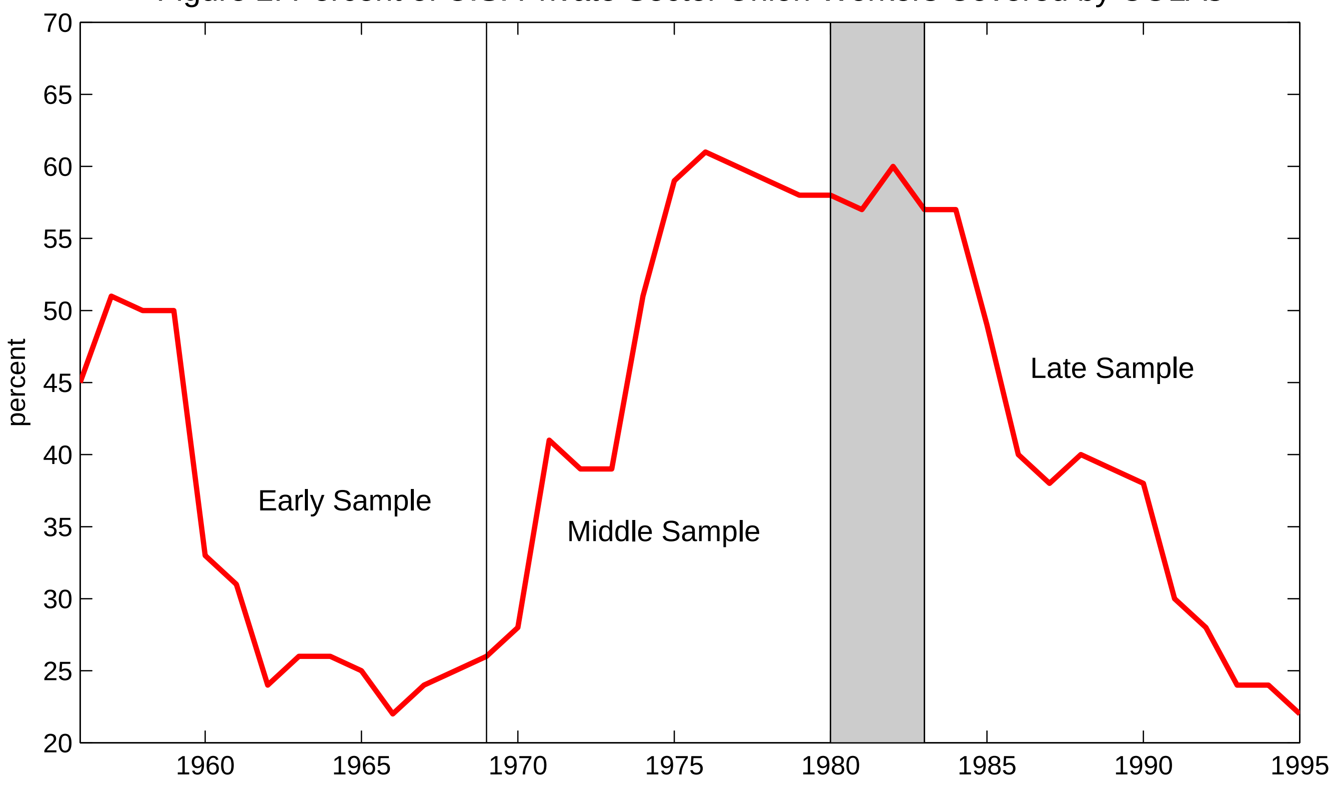
† Let Y_i denote the contribution of shock i to output so that $Y = \sum_{i=1}^{8} Y_i$ is the deviation of output from its trend. Then $\sigma_Y = \sum_{i=1}^{8} \rho_i \sigma_i$, where σ_Y and σ_i are the standard deviations of Y and Y_i, respectively, and where ρ_i is the correlation between Y and Y_i. Data from the first 25 percent of each sample are excluded from the calculations in order to minimize the role of pre-sample shocks. All of the results are in percentage points.
‡ Standard deviation of output.

Figure 1: Percent of U.S. Private Sector Workers Who Are Union Members



Sources: Hirsch (2008) and unionstats.com.

Figure 2: Percent of U.S. Private Sector Union Workers Covered by COLAs



Note: Weiner (1986) and Devine (1996) use different dating conventions. Observations dated Year T by Devine are dated Year T+1 by Weiner. We use Devine's dating notation since it appears in a Department of Labor publication. Sources: Weiner (1986) and Devine (1996).

Figure 3: Actual and Trend Inflation Rates

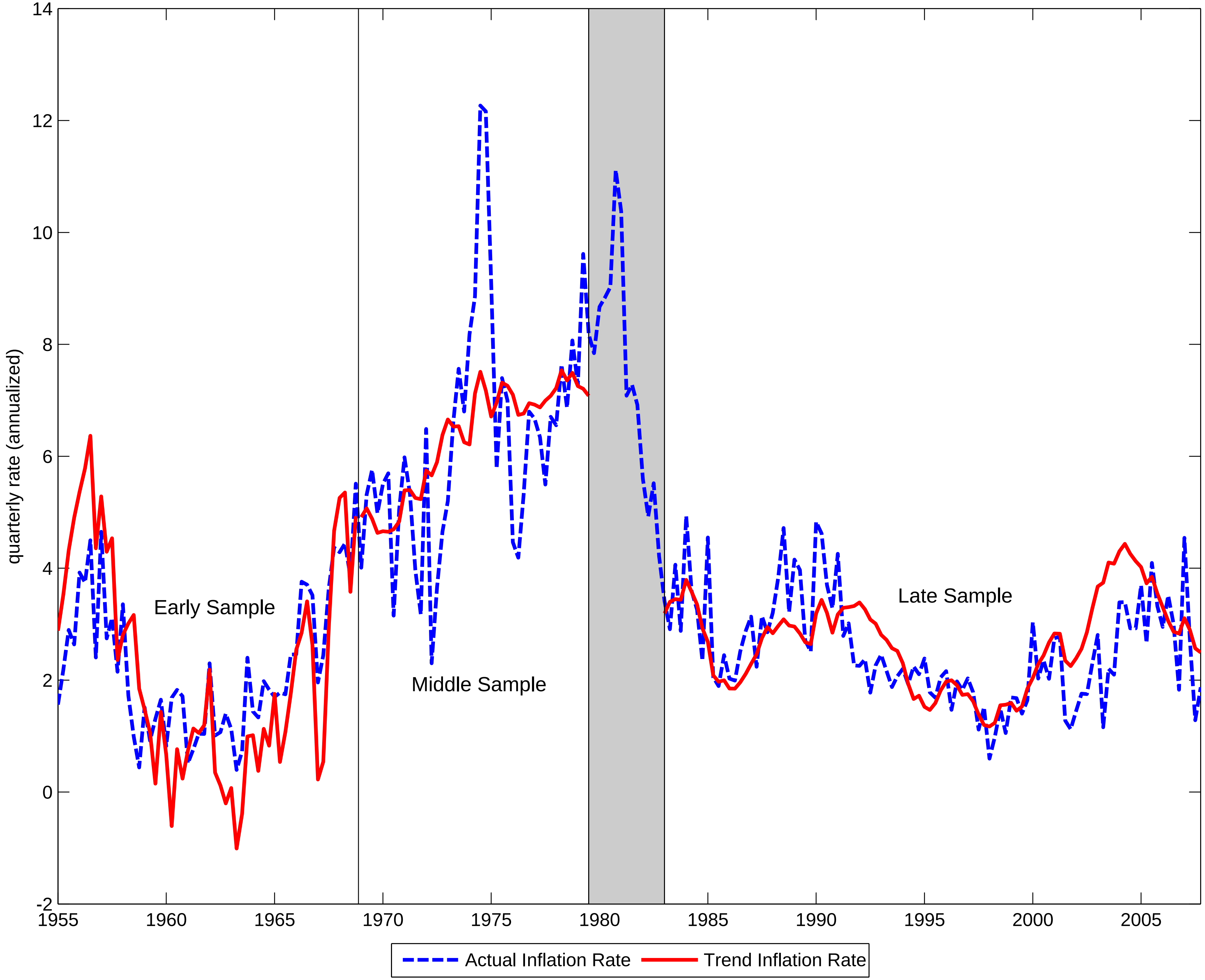


Figure 4A: Bayesian Impulse Responses to Exogenous Shocks

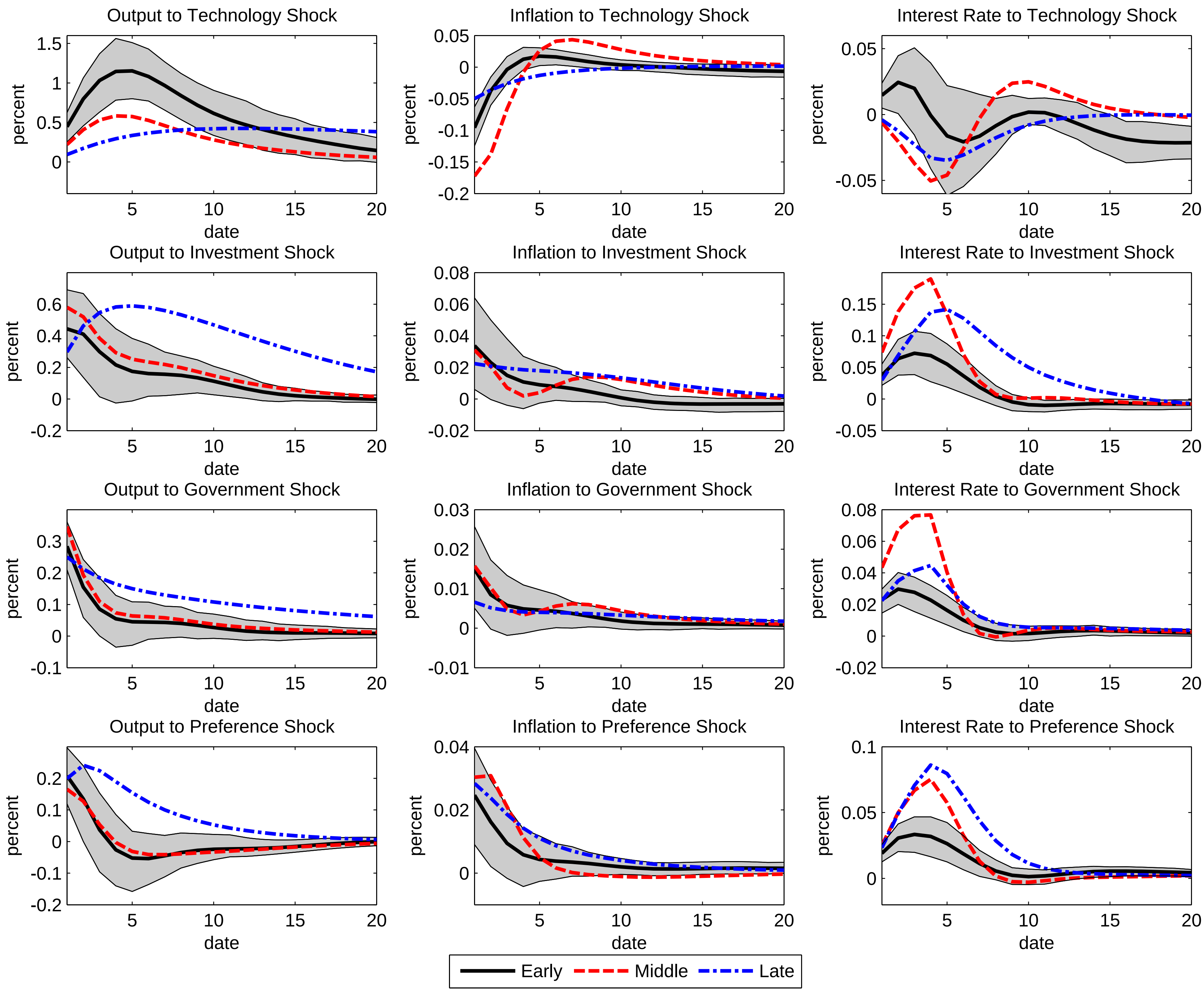


Figure 4B: Bayesian Impulse Responses to Exogenous Shocks