How Robust are Popular Models of Nominal Frictions?*

Benjamin D. Keen† University of Oklahoma

Evan F. Koenig‡ Federal Reserve Bank of Dallas

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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 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 samples. 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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†Benjamin D. Keen, Department of Economics, University of Oklahoma, 308 Cate Center Drive, 437 Cate Center One, Norman, OK 73019. Tel: (405) 325-5900. E-mail: ben.keen@ou.edu.

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

1 Introduction

1.1 Motivation and Main Results

Recently, economists have enjoyed considerable success constructing and estimating dynamic stochastic general equilibrium (DSGE) models that compete 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 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 prices can change every period, but each price is not optimized every period. The prices and wages that are not optimized increase automatically either by the steady-state inflation rate (static indexation) or by the 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 firms and households select price and wage paths that remain in force until the next optimization opportunity arises (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; and pre-set price and wage paths are sensible when inflation is variable, but 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 regarding technology, tastes, market structure, and real-side frictions. They differ, however, in their assumptions regarding price and wage adjustment. 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, 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

[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 fixed-price contracts will be updated more frequently as the average inflation rate rises.

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 the non-stationarity was the result of poorly conceived or badly executed monetary policy. Evidence from our early and late sample periods, in contrast, indicates 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 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. Our results suggest price-setting arrangements adjusted to that policy failure. Specifically, output prices were re-optimized somewhat more frequently during the middle period, and 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 multi-year labor union contracts. We also find that technology shocks had a far larger impact on output volatility during the middle sample than the early or late samples, and that monetary policy, as measured by 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. Our 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). Similarly, Murray, Nikolsko-Rzhevskyy, and Papell (2015) 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 non-

[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.

stationary.[6] According to both of those studies, non-stationary inflation behavior dominates our middle sample period (1969:Q1-1979:Q3), whereas inflation usually follows a stationary process in our early (1955:Q1-1968:Q4) and late (1983:Q1-2007:Q4) samples.

Many papers conclude that monetary policy mistakes are a major contributor to the drift in inflation observed during the 1970s. For example, Clarida, Gali, and Gertler (2000) find that pre-Volcker monetary policy failed to satisfy the Taylor-principle requirement that the short-term nominal interest rate responds by more than one-for-one to changes in inflation. Their data cover 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 the Taylor-principle requirement was not satisfied. As a result, monetary policy failed to anchor inflation. The authors suggest 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 (Orphanides, 2003). 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 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 the FOMC's policy of targeting money growth during the 1970s inadvertently 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 is low and reasonably stable from 1959-1966 and again from 1981-2000, but is high and generally rising from 1967-1979.[7][8] Similarly, the estimated persistence of inflation is notably 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 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

[6] In the same vein, Piger (2008) finds inflation persistence is 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."

compiled 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 in 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 resulted from 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 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 to 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 (Table 1). A few others separately analyze early- and late-sample estimates, but we are only aware of two previous studies (discussed below) that use a three-way 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. Moreover, 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 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 macroeconomic studies are not generally 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.

The analyses that best complement this paper are Hofmann, Peersman, and Straub (2012) and Bianchi (2013). Hofmann *et al.* examine the robustness of price and wage setting to shifts in the conduct of monetary policy, but use different methods and impose stronger assumptions than we do. Rather than estimate their DSGE model over three distinct sample periods, Hofmann et al. select model parameters that reproduce the impulse response functions from a time-varying-parameter VAR at three specific dates: 1960:Q1, 1974:Q1, and 2000:Q1. The DSGE model fit to those impulse response functions is not as rich as our

[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).

model because it excludes capital investment, does not consider sticky-information price and wage adjustment, and assumes technology and government purchases are the only sources of exogenous shocks in the economy. Their results differ from ours in several respects. Hofmann *et al.* uncover no evidence that the frequency with which prices and wages are re-optimized has changed over time. They also find the degree of price and wage indexation temporarily increases during the 1970s (specifically, in 1974), when monetary policy's response to inflation is weak. This paper, in contrast, finds evidence of a decline in wage indexation from the early sample to the middle sample as well as from the middle sample to the late sample. Our results also suggest the frequency with which prices and wages were re-optimized has changed over time: Wages were re-optimized with ever-increasing frequency, whereas the frequency of price re-optimization increased in the 1970s, when inflation was high and variable, and retreated in the Volcker-Greenspan era. Consistent with Hofmann et al., we find that price indexation is especially prevalent in the 1970s.

Bianchi (2013) constructs a DSGE model in which monetary policy switches between "hawk" and "dove" regimes, while shocks to the economy are either in a high-volatility or in a low-volatility regime. Agents take the possibility of regime change into account when forming expectations and making decisions. Although the model in principle allows for a total of four different regimes, in practice hawkish policy appears to be associated with the low-volatility regime and dovish policy with the high-volatility regime. Policy is dovish and shock volatility high from about 1970 through the early 1980s (closely matching our middle sample), and policy is hawkish and shock volatility is low from the mid-1950s through the 1960s (our early sample) and from the early 1980s through about 2006 (our late sample). Their DSGE model is fairly rich, with shocks to intertemporal preferences, the marginal efficiency of investment, technology, government purchases, and the conduct of monetary policy. They, however, do not explicitly model wage adjustment and do not consider sticky-information price adjustment. Bianchi also does not consider the impact of changes in the monetary authority's inflation target, the frequency of price re-optimization, or the degree of price indexation. Our paper examines different features of the economy than Bianchi (2013) and, as a result, generates some different results. Some of our different findings are that the de-anchoring of the Federal Reserve's inflation target is a distinguishing feature of the 1970s; the frequency of price re-optimization and degree of price indexation are important margins along which the private sector adjusts to shifts in policy regime; and the period from the mid-1950s through the late 1960s and the period from the late 1960s through the late 1970s are *both* "high-volatility" regimes, albeit for different reasons.

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 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 using 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:

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

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 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 households participate in a state-contingent securities market guaranteeing each household the same income, so all of the households make identical decisions regarding their remaining choice variables.[12]

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

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

Household h begins each period with its nominal money balances, M_{t-1}, carried over from last period and the 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, Hercowitz, and Huffman (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 implies 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 $\theta_{w,t}$ 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

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

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 each non-adjusting household to increase its 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), has each non-adjusting household raise its wage by the current steady-state inflation rate ($\gamma_w = 0$), while dynamic indexation, as in Christiano, Eichenbaum, and Evans (2005), has nominal wages 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 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 obtained easily using the first-order condition from the household's wage-setting problem and the aggregate nominal wage equation, (5):

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

[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.

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 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 $0 \leq \alpha \leq 1$. 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, $0 \leq \rho_Z < 1$, 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:

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

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

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 can be determined by combining (7) and (8):

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

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

Because 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 $\theta_{p,t}$ follows an ARMA(1,1) process:

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

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. In the sticky price specification, a 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 firms can optimally adjust their prices. Since opinions differ on how prices change for the $(1 - \eta_p)$ fraction of firms which cannot optimally adjust their prices, 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 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 that 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: The sticky-information price setting model, as in Koenig (1996, 1999), Mankiw and Reis (2002, 2007), and Keen (2007), rests on the assumption 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 that 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 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 four-quarter growth rate of output:

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

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

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

[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 four. We tried adding an output-gap term to the policy reaction function, but its coefficient was consistently small in magnitude and statistically insignificant.

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 follows 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 real gross domestic product, consumption is real personal consumption of nondurable goods 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, we assume 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^* is transferred then 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 each 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 used to obtain information on the posterior distribution.[18]

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 (2000) assumption that price and wage markups average 20 percent. Finally, the absence of a foreign sector in our model leads us to set government spending's average

[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.

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. Previous estimates of the labor-supply elasticity range from 0 to ∞, so we transform the inverse of the elasticity of labor supply with respect to the real wage, ζ, and assume that $1/(1+\zeta)$ 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 $\phi_{\Delta y_4}$.

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 with 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 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 our early-sample data were generated by a model with dynamic wage adjustment and static price adjustment (0.487) are roughly seven times greater than a model with static wage and static price adjustment (0.070). In our late sample, however, Panel C reveals the dynamic-wage/static-price model (0.101) is only 1/5 as likely to have generated the data as the static-wage/static-price model (0.491).

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 0.963 and 0.972, respectively, dominates alternative models of nominal price setting. That result has intuitive appeal given the abundance of evidence from prior studies suggesting monetary policy anchored inflation expectations during those periods. In the middle sample, our results suggest 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 80 percent ($0.431 + 0.366 = 0.797$). As previously argued, price indexation is a reasonable response when aggregate inflation follows a non-stationary process, as was the case in the U.S. 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 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 0.503 in the early sample to 0.103 in the late sample, whereas they correspondingly rise from 0.075

to 0.506 for static wage indexation. In contrast, the posterior probabilities for models with partial wage indexation hold relatively steady over time with 0.415 in the early sample and 0.390 in the late sample. The relative similarity of monetary policy in the early and late samples means 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 monetary policy that failed to anchor 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 the posterior probabilities for sticky-information wages gain at the expense of dynamic wage indexation. A comparison of Panels B and C shows posterior probabilities attached to models with static wage indexation are much higher in the late sample period than in the middle sample period. That shift toward static indexation 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. Using that price-friction model, dynamic 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 data consistent than are other approaches. Accordingly, our baseline price and wage frictions models are static price indexation and dynamic 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.

4.3 Baseline Parameter Estimates

To obtain more precise estimates of the policy, price-setting, and wage-setting parameters that are of greatest interest to us, we undertake a second, restricted estimation of our baseline models. In the restricted estimation, a small number of production and preference parameters are fixed at their first-round, cross-sample-average values. There is no *a priori* reason to believe those parameters vary over time, and our first-round estimates are consistent with that hypothesis.[20] Second-round parameter estimates are displayed in Table 4A. Each estimate is the mean value of that parameter's posterior distribution over the specified sample period, where that distribution is generated using the Metropolis-Hastings algorithm. To convey a sense of the uncertainty attached to our estimates, we also report the 5th and 95th percentiles for each parameter's posterior distribution.

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

[20] We restricted three parameters: capital's share of output in the production function (α in Equation 6), the habit-persistence parameter in the household utility function (b in Equation 1), and the labor-supply elasticity $[1/(1+\zeta)$ in Equation 1]. For α, early, middle, and late-sample estimates (and standard errors) were 0.2614 (0.0161), 0.2510 (0.0217), and 0.2243 (0.0160), respectively; for b, early, middle, and late-sample estimates were 0.6730 (0.0975), 0.7106 (0.0562), and 0.8418 (0.0401), respectively; and for $1/(1+\zeta)$, early, middle, and late-sample estimates were 0.8206 (0.0905), 0.8123 (0.1002), and 0.7584 (0.1190). For each parameter, the greater the relative precision of a given estimate, the greater the weight given that estimate when calculating the cross-sample mean.

Our estimates for the inflation-target and policy-rate shock processes provide a glimpse into the conduct of monetary policy during our three sample periods. They suggest policy was relatively loosely tied to output growth and inflation in our middle sample, as evidenced by the much larger standard deviation of the policy-rate shock: 0.0026 versus 0.0007 and 0.0008, respectively, in our early and late samples. Policy also reacted more sluggishly to real growth and inflation during the 1970s: $\phi_{R_1} + \phi_{R_2} = 0.85$ in the middle sample, as compared to $\phi_{R_1} + \phi_{R_2} = 0.41$ and $\phi_{R_1} + \phi_{R_2} = 0.69$ in the early and late samples, respectively. Inflation-target shocks are about equally persistent in the early and late samples ($\rho_\pi = 0.68$ and $\rho_\pi = 0.78$, respectively), but follow a unit-root process in the middle sample (*c.f.* footnote #17). Furthermore, the standard deviation of the inflation-target shock declines by over 1/3 from the early sample to the middle sample and by another 1/4 as one moves to the late sample. Our estimates imply that longer-run inflation expectations went from being loosely anchored (early sample), to unanchored (middle sample), to well anchored (late sample). Those findings are broadly consistent with the existing literature, as discussed in the introductory sections of this paper.

To illustrate inflation's behavior, Figure 3 compares realized annualized quarterly inflation (blue dashed line) with the inflation target (red solid line) derived from estimated shocks to the inflation target process. Our estimates show the target inflation rate drifted upward during the 1970s and exhibited an elevated level of volatility in the early sample. It also reveals the target inflation rate rose in 2003 and 2004, which signals that the policy rate was held lower over this period than would have been consistent with stable inflation. Taylor (2012) calls this policy shift the "Great Deviation".

In addition to changes in price and wage indexing among samples, Table 4A provides evidence that the frequency of price and wage re-optimizations has changed over time. The frequency of wage re-optimization, η_w, increases from 0.23 in the early sample, to 0.28 in the middle sample, and to 0.33 in the late sample. This gradual drift toward greater flexibility plausibly reflects the shrinking importance of unions and their multi-year labor contracts as shown in Figure 1. In contrast, the frequency of price re-optimizations, η_p, increases by nearly 1/3 between the early and middle samples and then falls by 1/2 in the late sample. The variation in those estimates seems to be driven primarily by how well monetary policy anchored longer-run inflation expectations in each sample.

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 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. The net result is that the unconditional standard deviation of government spending is somewhat lower in the middle sample than in the late sample. 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 slightly larger in the late sample. The unconditional standard deviations for most of the other exogenous variables vary substantially across periods. For instance, the unconditional standard deviation of the price markup parameter, $\theta_{p,t}$, is nearly 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 less than half as large in the late sample as in the early sample.

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 multifactor technology and investment-efficiency shocks (hereafter, "technology shocks") are a major source of output variation at all horizons and across all three of our sample periods. In Table 5, the fraction of output fluctuations explained by technology shocks ranges from a minimum of 36.8 percent to a maximum of 63.1 percent. Technology shocks are particularly important in our middle sample period, where their contribution is never less than 59.5 percent. Early-sample and late-sample contributions, in contrast, never exceed 46.1 percent. Markup shocks also are an important source of output variation across all horizons and sample periods but, unlike technology shocks, have a *smaller* impact in our middle sample period than in our early and late samples. In the middle sample, the fraction of output movements explained by markup shocks rises from 8.0 percent, to 22.6 percent, to 25.3 percent as the forecast horizon, H, is extended from 1 to 4 to ∞. Their corresponding contributions to output variability are larger at 22.3, 35.4, and 51.5 percent in the early sample and 27.4, 44.7, and 49.0 percent in the late sample. Inflation-target and policy-rate shocks (hereafter, "policy shocks") are a major driver of output fluctuations only in our early sample period, where their contribution falls from 20.5 percent at $H = 1$ to 19.8 percent and 10.0 percent at $H = 4$ and $H = \infty$, respectively. Finally, government-spending and preference shocks are important sources of output variation only at the shortest horizons in our middle and late sample periods. To summarize, technology shocks explain the majority of output movements in our middle sample, markup shocks have their greatest impact on output in our early and late samples, and government-spending and preference shocks mainly impact output in our middle and late samples. Monetary-policy shocks, on the other hand, only have any sizable impact on output variability in our early sample. The implications of those results for the factors behind the post-1983 Great Moderation of output are discussed next, in Section 5.2.

Table 5 reveals the sources of inflation variation drastically change between our early and late samples. Focusing on the 4-quarter forecast horizon, policy shocks–especially shocks to the inflation target–explain 47.2 percent of inflation movements in the early sample but only

13.4 percent in the late sample. Similarly, technology shocks' impact on inflation variability falls from 25.3 percent in the early sample to just 9.0 percent in the late sample. This pattern is reversed for markup shocks. Their contribution to inflation volatility increases from 25.2 percent in our early sample to 73.7 percent in our late sample. Government-spending and preference shocks, on the other hand, have no meaningful impact on inflation in either the early or late sample periods.

The variance decompositions for the nominal interest rate, like those for inflation, can only be compared between the early and late samples. We begin by analyzing those variance decompositions at a 4-quarter forecast horizon. Technology shocks–especially investment efficiency shocks–account for 63.4 percent of interest rate fluctuations in the early sample but their contribution drops to 35.6 percent in our late sample. The pattern for markup shocks is just the opposite. Their impact on interest rate fluctuations is 6.2 percent in the early sample, while their late sample contribution is 31.7 percent. Monetary-policy shocks have roughly the same impact on interest rate movements in the early and late samples. That is, they account for 10.2 percent of variation in the early sample and 10.9 percent in the late sample. Government-spending shocks diminish somewhat in importance moving from the early sample to the late sample, while preference shocks increase in importance. Thus, the total contribution from these two sources remains fairly constant, rising only from 20.2 percent in the early sample to 21.8 percent in the late sample. Our finding that technology shocks have a smaller impact on interest rate movements over time, while markup shocks have a larger influence is robust to the shorter and longer forecast horizons of $H = 1$ and $H = \infty$. The length of the forecast horizon, however, does affect which types of shocks have the greatest influence on interest rate movements. Specifically, policy-rate shocks account for the majority of the variation in interest rates at $H = 1$, while technology shocks are the main source of interest-rate variability at $H = 4$ and $H = \infty$.

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 began in the early 1980s (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 2.4 percentage points in the early and middle samples but falls by 1/3 to 1.6 percentage points in the late sample. Our model suggests 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 shows all of the reduction in output volatility across the two periods can be attributed to monetary policy. Specifically, inflation-target shocks raise the standard deviation of output by nearly one percentage point in the early sample, but lower the standard deviation of output by 35 basis points in the late sample. In contrast, technology and markup shocks make somewhat larger contributions to output fluctuations in the late sample than in the early sample.

A similar analysis of the middle and late samples reveals output volatility declined due to a sizable reduction in the contribution from multifactor technology shocks. Those shocks raise the standard deviation of output by 95 basis points in the middle sample, but then lower the standard deviation of output by 17 basis points in the late sample. Most of the other exogenous shocks either help moderate the decline in output volatility from the middle to late sample or have little effect. Thus, whether the Great Moderation in output volatility should be attributed mostly to "luck" (reduced volatility in technology shocks) or mostly to improved monetary policy depends on whether the Great Moderation period is being compared to the 1970s or to the late 1950s through most of the 1960s.

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 output responds as expected to each shock. Positive shocks to multifactor technology, investment efficiency, government spending, preferences, and the inflation target all cause near-term output to increase.[21] In contrast, output immediately declines in response to positive shocks to the price markup, the wage markup, and the policy rate.[22] 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. The impulse response functions for output are affected by our estimates of the standard deviation and persistence of the exogenous shocks. Multifactor technology shocks, for example, are smaller and more persistent in the late sample than in the early and middle samples. As a result, output's response to a multifactor technology shock in the late sample is initially weaker but more persistent. Investment-efficiency shocks are estimated to be especially small in the early sample and very persistent in the late sample. Those estimates cause output's response to an investment efficiency shock to be modest and peak on impact in the early sample and to be more long-lasting and hump-shaped in the late sample. In general, the smoother and, in some cases, weaker impulse responses observed for output in the late sample are consistent with the reduced high-frequency variation in output that defines the

[21] A preference shock is slightly different from a discount-factor shock. A positive preference shock indicates 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.

[22] 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.

Great Moderation. A comparison of impulse responses reveals preference and wage markup shocks are the only exogenous disturbances that generate an unambiguously 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 investment efficiency, government spending, preferences, 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 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 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 its target, which explains why inflation's response in Figure 4B is initially negative. Inflation continues to rise in subsequent periods, by enough that it overshoots its target for a time. 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 response to exogenous shocks is generally similar across sample periods. One exception is that policy shocks generate a much stronger inflation response in the middle sample than in either the early or late samples. Also, inflation has a tendency to overshoot target inflation in the middle sample. This tendency is evident in inflation's response to shocks to multifactor technology, preferences, price and wage markups, and–as previously noted–to the inflation target itself. Consistent with this propensity to overshoot, inflation's middle-sample response to multifactor-technology, price-markup, and wage-markup shocks is initially stronger than in the early and late samples. In contrast, all of inflation's late-sample impulse responses peak on impact and then monotonically return to steady state without overshooting. The contrasting middle-sample and late-sample responses of inflation to multifactor-technology shocks are consistent with the notion the FOMC routinely accommodated commodity-price increases (a particular type of negative multifactor-technology shock) during the 1970s, but rarely, if ever, did so during the Great Moderation.[23]

The impulse responses for the nominal interest rate fluctuate significantly more in the middle sample than in the early sample.[24] The larger response occurs even when output and inflation behave similarly across the two samples, as is the case for investment-efficiency,

[23] "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 (2015) 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.

[24] 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.

government-spending, and preference shocks. Two factors driving these dynamics are the somewhat stronger response of monetary policy to output growth in the middle sample and the greater emphasis on interest-rate smoothing ($\phi_{R_1} + \phi_{R_2}$ is larger). The relatively large estimate for the standard deviation of ε_R also contributes to policy-rate shocks having a greater impact on interest rates in the middle sample.

The estimated policy rule coefficients on output and inflation ($\phi_{\triangle y_4}$ and ϕ_π) are similar in the early and late sample periods, so any differences in the interest rate's impulse responses between the samples is mostly explained by differences in the responses of output and inflation. For example, government-spending and policy-rate shocks have similar impacts on output and inflation in the early and late samples, so their corresponding effects on the nominal interest rate are also similar. Preference and price-markup shocks, in contrast, have different impacts on inflation in the early and late samples. That disparity causes those shocks to produce different impulse responses for the nominal interest rates across those samples.

6 Summary and Suggestions for Future Research

Our results indicate 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 a model with static price indexation and dynamic 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 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 model with static price and wage indexation during a time characterized by low unionization rates and a monetary policy with a strong inflation anchor. Changes across samples in the frequency with which wages and prices have been re-optimized are evident, too. As unionization has declined, wages have become gradually less and less "sticky." The frequency of price re-optimization, in contrast, appears sensitive to the conduct of monetary policy: Prices were least sticky in the 1970s, when policy failed to anchor inflation, and most sticky in the late sample, when policy provided the strongest 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 valid approximations only in a quite limited range of institutional and policy environments.

Two additional findings from this paper are important and worth reiterating. First, 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: Improved monetary policy is mainly responsible for reduced volatility relative to our early sample, and smaller technology shocks are mainly responsible for reduced volatility relative to our middle sample. Second, inflation is much less sensitive to multifactor-technology shocks in the late sample than in the middle sample—a result 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 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. He finds that firms completely index to the inflation-rate target and place zero weight on lagged inflation. That result is consistent with our conclusion that the sophistication of price setting by firms is not adequately captured by the standard sticky-price and sticky-information models. Similarly, Davig and Doh (2014) assume prices are indexed to trend inflation between re-optimizations and that monetary policy switches between dovish and hawkish regimes. Firms then account for the possibility of a regime change when optimizing their prices.

A second approach for future research is to carefully model the endogeneity of nominal frictions to determine the circumstances in which one pricing specification is likely to be preferred to alternatives. For example, 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.[25] Once those shifting weights are taken into account, they find no evidence of dynamic indexation in the data: Firms appear to hold their prices constant between re-optimizations.

[25] Similarly, 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.

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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†

Parameters		Prior Distribution
Technology & Preferences		
α	Capital's Share of Output	Normal(0.3,0.05)
κ	Investment Adjustment Costs	Normal(4,1.5)
b	Habit Persistence	Beta(0.7,0.15)
$\frac{1}{(\zeta+1)}$	Labor Supply Elasticity	Beta(0.75,0.15)
Price & Wage		
η_p	Price Adjustment Probability	Beta(0.25,0.1)
η_w	Wage Adjustment Probability	Beta(0.25,0.1)
γ_p	Price Indexation	Beta(0.5,0.2)
γ_w	Wage Indexation	Beta(0.5,0.2)
Taylor Rule		
ϕ_{R_1}	Interest Rate (t-1)	Uniform(-2,2)
ϕ_{R_2}	Interest Rate (t-2)	Uniform(-2,2)
ϕ_{π}	Inflation Rate	Uniform(0,2)
$\phi_{\Delta y_4}$	4-Quarter Output Growth	Uniform(-1,1)
Shock Processes		
ρ_Z	Autocorr. Multifactor Tech. Shock	Beta(0.5,0.2)
ρ_J	Autocorr. Invest. Efficiency Shock	Beta(0.5,0.2)
ρ_G	Autocorr. Gov't Spending Shock	Beta(0.5,0.2)
ρ_a	Autocorr. Preference Shock	Beta(0.5,0.2)
ρ_p	Autocorr. Price Markup Shock	Beta(0.5,0.2)
ρ_w	Autocorr. Wage Markup Shock	Beta(0.5,0.2)
ρ_{π}	Autocorr. Inflation Target Shock	Beta(0.5,0.2)
μ_p	Moving Avg. Price Markup Shock	Beta(0.5,0.2)
μ_w	Moving Avg. Wage Markup Shock	Beta(0.5,0.2)
σ_Z	Std. Dev. Multifactor Tech. Shock	Inv-Gamma(0.01,2)
σ_J	Std. Dev. Invest. Efficiency Shock	Inv-Gamma(0.01,2)
σ_G	Std. Dev. Gov't Spending Shock	Inv-Gamma(0.01,2)
σ_a	Std. Dev. Preference Shock	Inv-Gamma(0.01,2)
σ_p	Std. Dev. Price Markup Shock	Inv-Gamma(0.1,2)
σ_w	Std. Dev. Wage Markup Shock	Inv-Gamma(1,2)
σ_{π}	Std. Dev. Inflation Target Shock	Inv-Gamma(0.005,2)‡
σ_R	Std. Dev. Policy Rate Shock	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	0.070	0.004	0.000	0.001	0.075
Partial	0.400	0.015	0.000	0.000	0.415
Dynamic	0.487	0.015	0.000	0.001	0.503
Sticky Info.	0.006	0.000	0.000	0.000	0.006
Total	0.963	0.034	0.000	0.002	1.000

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

Wage\Price	Static	Partial	Dynamic	Sticky Info.	Total
Static	0.023	0.046	0.033	0.001	0.103
Partial	0.086	0.214	0.176	0.013	0.489
Dynamic	0.038	0.071	0.051	0.015	0.175
Sticky Info.	0.022	0.100	0.106	0.003	0.231
Total	0.169	0.431	0.366	0.032	1.000

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

Wage\Price	Static	Partial	Dynamic	Sticky Info.	Total
Static	0.491	0.014	0.000	0.001	0.506
Partial	0.380	0.009	0.000	0.001	0.390
Dynamic	0.101	0.002	0.000	0.000	0.103
Sticky Info.	0.000	0.000	0.000	0.000	0.000
Total	0.972	0.025	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	–	$\equiv 0.2445$	–	–	$\equiv 0.2445$	–	–	$\equiv 0.2445$	–
b	–	$\equiv 0.7850$	–	–	$\equiv 0.7850$	–	–	$\equiv 0.7850$	–
$\frac{1}{(\zeta+1)}$	–	$\equiv 0.8027$	–	–	$\equiv 0.8027$	–	–	$\equiv 0.8027$	–
κ	0.1003	0.3978	0.7288	0.4959	1.8642	3.2081	3.2931	5.0665	6.8451
Price & Wage									
η_p	0.1837	0.2269	0.2676	0.2386	0.3168	0.3914	0.1133	0.1553	0.1976
η_w	0.1475	0.2322	0.3089	0.1940	0.2843	0.3704	0.2123	0.3301	0.4326
γ_p	–	$\equiv 0$	–	0.1749	0.4892	0.8141	–	$\equiv 0$	–
γ_w	–	$\equiv 1$	–	0.2271	0.5106	0.8068	–	$\equiv 0$	–
Taylor Rule									
ϕ_{R_1}	0.5157	0.8832	1.2356	0.8673	1.1260	1.3854	0.6989	0.9144	1.1352
ϕ_{R_2}	−0.7414	−0.4709	−0.1948	−0.6070	−0.2793	0.0462	−0.3975	−0.2274	−0.0537
ϕ_π	0.1639	0.7857	1.5534	0.1059	0.5485	0.9909	0.4224	0.7291	1.0060
$\phi_{\Delta y_4}$	0.1096	0.2337	0.3693	0.1456	0.3678	0.5688	0.1570	0.2638	0.3676
Shock Processes									
ρ_Z	0.8186	0.8741	0.9328	0.6856	0.7971	0.9112	0.9470	0.9679	0.9894
ρ_J	0.1583	0.4270	0.7076	0.0993	0.3052	0.4954	0.6203	0.7265	0.8346
ρ_G	0.7119	0.8172	0.9329	0.6702	0.7967	0.9292	0.9100	0.9436	0.9806
ρ_a	0.1071	0.2764	0.4387	0.2441	0.4383	0.6293	0.5036	0.6371	0.7692
ρ_p	0.9065	0.9460	0.9889	0.3391	0.5938	0.8432	0.8251	0.8856	0.9486
ρ_w	0.1399	0.3853	0.6274	0.2195	0.4844	0.7458	0.7490	0.8799	0.9800
ρ_π	0.5487	0.6803	0.8075	–	$\equiv 1$	–	0.6318	0.7807	0.9233
μ_p	0.3656	0.5733	0.7912	0.1410	0.4165	0.6761	0.3770	0.5740	0.7809
μ_w	0.3299	0.5426	0.8071	0.1535	0.4561	0.7244	0.5215	0.7009	0.8705
σ_Z	0.0066	0.0079	0.0091	0.0063	0.0076	0.0089	0.0042	0.0047	0.0053
σ_J	0.0036	0.0129	0.0243	0.0218	0.0739	0.1222	0.0348	0.0559	0.0749
σ_G	0.0032	0.0038	0.0044	0.0039	0.0047	0.0055	0.0025	0.0028	0.0031
σ_a	0.0176	0.0211	0.0243	0.0140	0.0178	0.0214	0.0134	0.0160	0.0184
σ_p	0.0562	0.0950	0.1348	0.0634	0.1315	0.2004	0.1027	0.2207	0.3367
σ_w	0.5001	1.6769	3.0050	0.2723	0.8131	1.3513	0.2215	0.5660	1.0055
σ_π	0.0019	0.0034	0.0050	0.0011	0.0019	0.0028	0.0008	0.0014	0.0020
σ_R	0.0005	0.0007	0.0008	0.0020	0.0026	0.0031	0.0006	0.0008	0.0009

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	–	0.0163	–	–	0.0126	–	–	0.0187	–
Σ_J	–	0.0143	–	–	0.0776	–	–	0.0799	–
Σ_G	–	0.0066	–	–	0.0078	–	–	0.0085	–
Σ_a	–	0.0220	–	–	0.0198	–	–	0.0208	–
Σ_p	–	0.1448	–	–	0.1347	–	–	0.2658	–
Σ_w	–	1.7011	–	–	0.8135	–	–	0.6048	–
Σ_π	–	0.0040	–	–	$\equiv \infty$	–	–	0.0022	–
Σ_R	–	0.0007	–	–	0.0026	–	–	0.0008	–

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

Table 5: Forecast Error Variance Decompositions

Panel A: $H = 1$	Output			Inflation Rate			Interest Rate		
Shock Process	55-68	69-79	83-07	55-68	69-79	83-07	55-68	69-79	83-07
Multifactor Tech.	17.10	6.07	4.22	25.91	22.80	5.45	3.69	0.12	0.44
Invest. Efficiency	25.56	54.13	32.62	3.57	0.66	1.04	24.66	4.02	8.05
Gov't Spending	9.05	20.46	19.94	0.55	0.23	0.08	6.83	1.51	3.59
Preference	5.50	4.86	12.27	1.46	0.82	2.29	6.77	0.54	5.25
Price Markup	20.11	5.46	16.28	35.48	63.09	71.03	6.13	1.06	13.57
Wage Markup	2.22	2.54	11.11	6.35	9.08	13.87	1.72	0.05	1.06
Inflation Target	20.20	2.92	3.35	26.67	1.61	6.20	0.03	34.96	0.28
Policy Rate	0.26	3.58	0.19	0.01	1.70	0.04	50.18	57.75	67.76

Panel B: $H = 4$	Output			Inflation Rate			Interest Rate		
Shock Process	55-68	69-79	83-07	55-68	69-79	83-07	55-68	69-79	83-07
Multifactor Tech.	32.23	23.42	7.74	20.76	29.09	6.76	7.87	2.57	1.63
Invest. Efficiency	9.69	36.07	32.69	4.54	0.66	2.21	55.52	26.66	33.93
Gov't Spending	1.77	7.31	4.86	0.65	0.26	0.12	8.02	5.75	4.40
Preference	1.11	2.34	5.82	1.68	1.47	3.82	12.13	4.56	17.38
Price Markup	32.24	12.70	24.64	21.09	49.00	53.98	3.55	7.10	26.40
Wage Markup	3.13	9.92	20.07	4.06	12.02	19.73	2.67	1.01	5.33
Inflation Target	19.77	4.17	4.08	47.21	2.63	13.31	1.09	18.50	0.70
Policy Rate	0.06	4.06	0.10	0.01	4.87	0.07	9.15	33.84	10.23

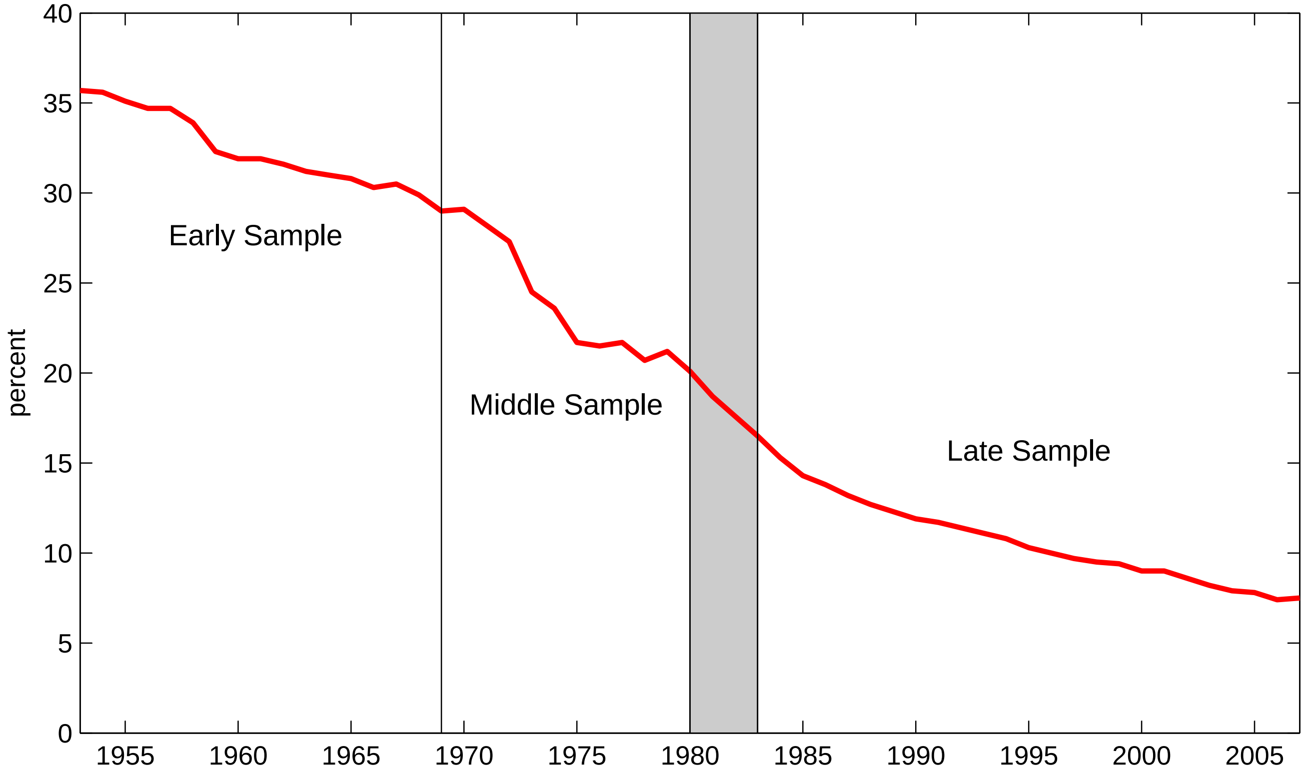
Panel C: $H = \infty$	Output			Inflation Rate			Interest Rate		
Shock Process	55-68	69-79	83-07	55-68	69-79	83-07	55-68	69-79	83-07
Multifactor Tech.	33.53	35.54	26.65	19.10	30.07	6.29	12.17	4.44	2.08
Invest. Efficiency	4.00	27.53	19.46	4.46	1.17	4.82	41.84	30.54	45.99
Gov't Spending	0.63	4.39	1.63	0.72	0.32	0.29	5.61	5.55	2.77
Preference	0.37	1.44	1.08	1.60	1.28	3.95	8.94	5.71	15.80
Price Markup	49.43	10.17	22.16	20.49	47.32	47.94	16.53	7.90	19.20
Wage Markup	2.04	15.17	26.89	3.57	12.50	19.08	2.29	1.82	8.69
Inflation Target	9.98	3.08	2.12	50.06	2.82	17.56	6.49	15.60	0.63
Policy Rate	0.02	2.67	0.02	0.01	4.51	0.07	6.14	28.43	4.84

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	**0.255**	**0.014**	**−0.064**
Technology			
Multifactor Tech.	0.062	0.946	−0.171
Invest. Efficiency	0.238	0.668	0.899
Subtotal	**0.300**	**1.614**	**0.728**
Gov't & Preference			
Gov't Spending	0.165	0.131	0.335
Preference	0.149	0.019	−0.129
Subtotal	**0.314**	**0.150**	**0.206**
Markup			
Price Markup	0.213	0.439	0.625
Wage Markup	0.385	0.275	0.463
Subtotal	**0.598**	**0.714**	**1.088**
Monetary Policy			
Inflation Target	0.924	0.016	−0.351
Policy Rate	−0.003	−0.138	−0.013
Subtotal	**0.921**	**−0.122**	**−0.364**
Total Volatility‡	**2.388**	**2.370**	**1.594**

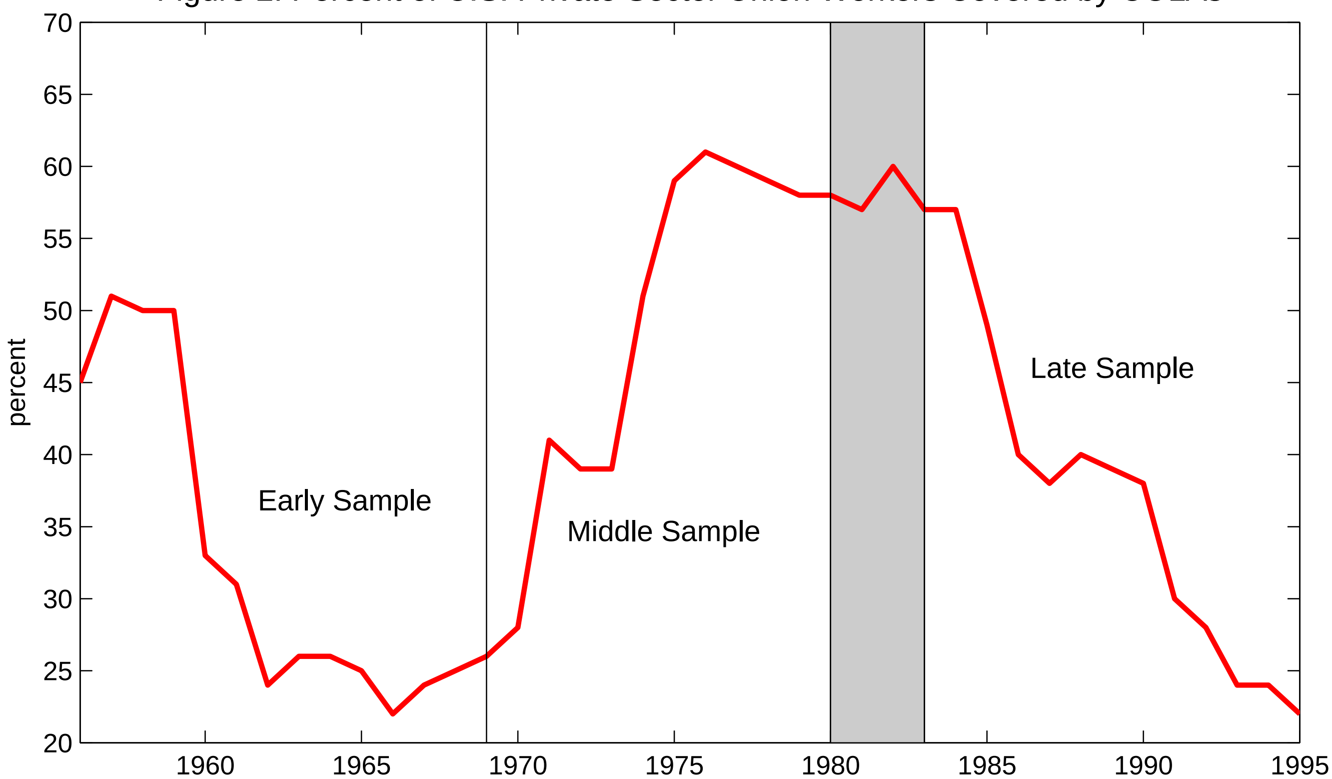
† Let Y_i denote the contribution of shock i to output so that $Y = \sum_{i=1}^{8} Y_i$ is the deviation of output from its trend. Then $\sigma_Y = \sum_{i=1}^{8} \rho_i \sigma_i$, where σ_Y and σ_i are the standard deviations of Y and Y_i, respectively, and where ρ_i is the correlation between Y and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



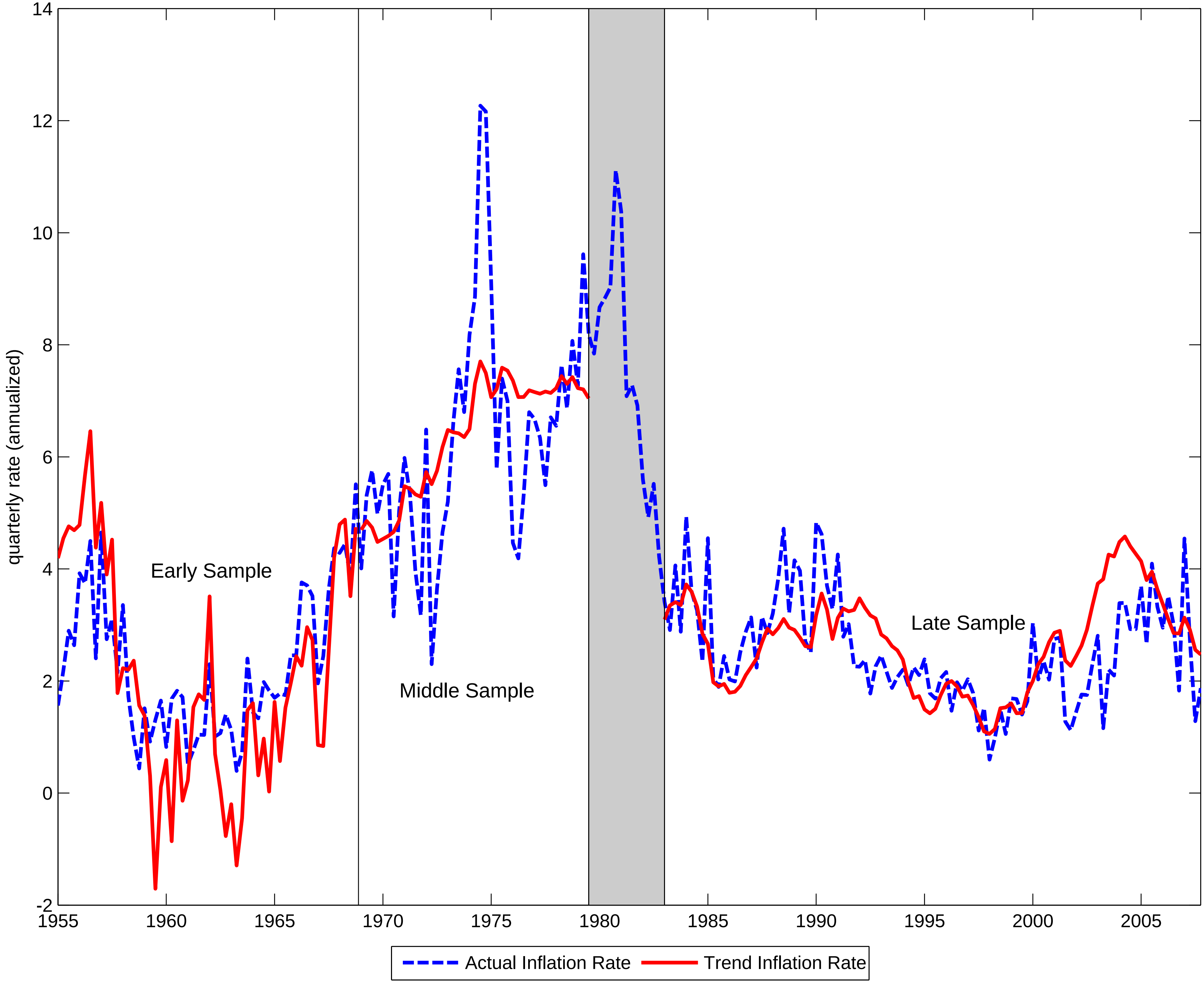
Sources: Hirsch (2008) and unionstats.com.

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



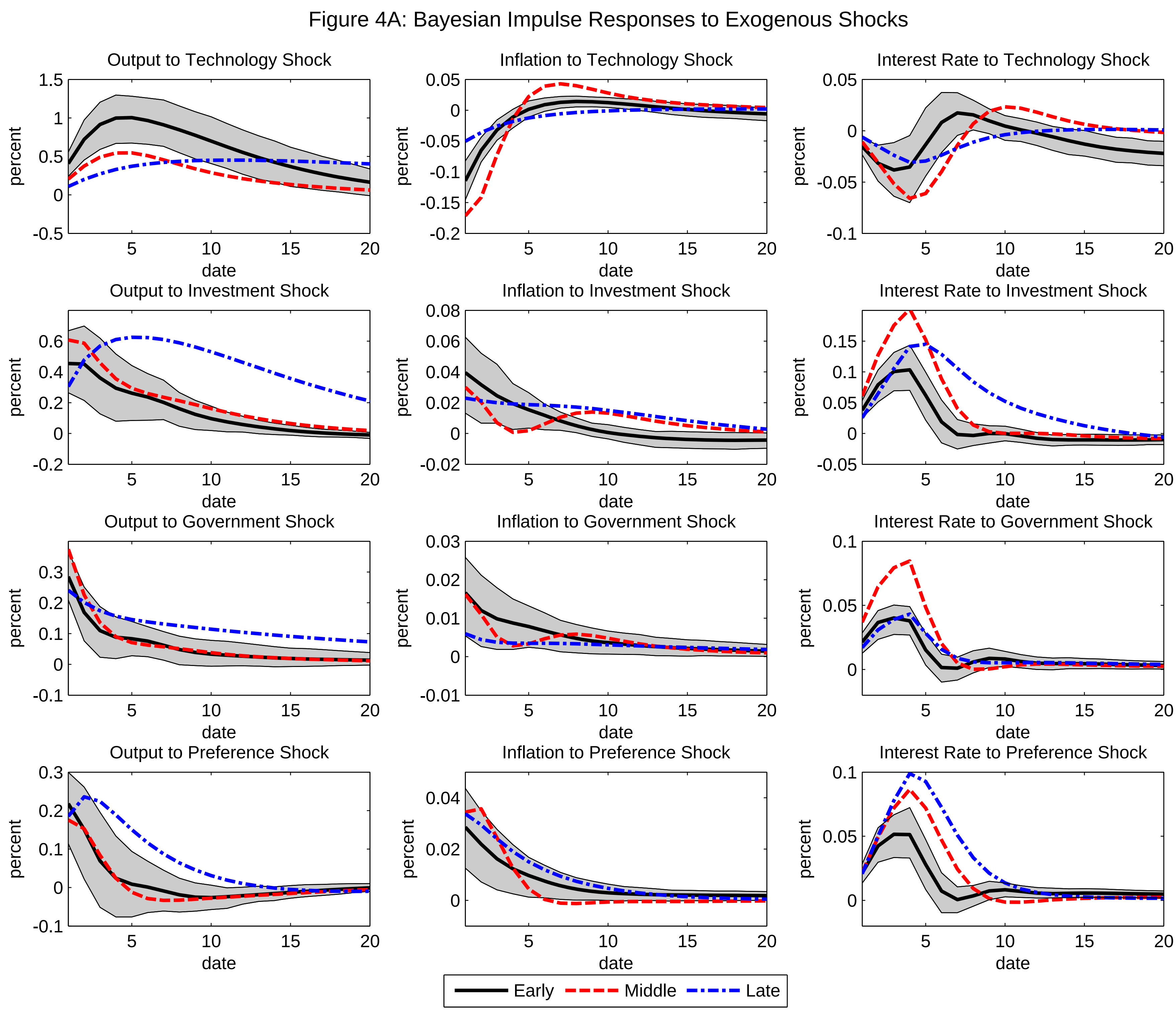


Figure 4A: Bayesian Impulse Responses to Exogenous Shocks
Output to Technology Shock
Inflation to Technology Shock
Interest Rate to Technology Shock
Output to Investment Shock
Inflation to Investment Shock
Interest Rate to Investment Shock
Output to Government Shock
Inflation to Government Shock
Interest Rate to Government Shock
Output to Preference Shock
Inflation to Preference Shock
Interest Rate to Preference Shock
percent
date
Early
Middle
Late

Figure 4B: Bayesian Impulse Responses to Exogenous Shocks