# Optimal Monetary Policy in an Estimated New Keynesian Model with Heterogenous Sectors

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**Abstract** I develop a multisector New Keynesian dynamic stochastic general equilibrium model incorporating heterogeneities in the sector size, price stickiness, price indexation, and the price markup. I estimate a 12-sector version with post-1984 US data using Bayesian techniques. The estimates suggest that over the sample period the Federal Reserve (the Fed) did not respond to changes in the prices of gasoline and other energy goods or changes in the price of health care, yet responded relatively more aggressively to changes in the prices of housing and utilities. I obtain multiple welfare-maximizing monetary policy schemes via simulation. The optimal schemes suggest that the Fed should focus on the prices of food and beverages as well as the prices of housing and utilities when responding to inflation. However, the welfare gains are small, suggesting that the current inflation target adopted by the Fed is almost indistinguishable from the optimal one in terms of welfare. On the other hand, more aggressive targeting of the output gap can offer much larger welfare improvement.

**Keywords** Bayesian analysis, DSGE, heterogeneity, inflation targeting, monetary policy, multisector model, New Keynesian

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## 1 Introduction

Under the monetary policy regime known as "inflation targeting," a central bank explicitly announces a quantitative inflation target that it commits to achieve over some time horizon, usually the medium or the long term.[1] Although there is much consensus on what the level or the range of the inflation target should be,[2] central banks and researchers diverge on from which price index the inflation target should be calculated. Common choices include variants of "core" inflation, which exclude prices in certain categories in computing the overall inflation rate.[3] For instance, before the Federal Reserve (the Fed) announced an explicit inflation target of 2% as measured by the annual change in the price index for personal consumption expenditures (PCE) on January 25, 2012, the core PCE inflation rate, which is the PCE inflation rate computed without food and energy prices,[4] was favored by the Fed, though not explicitly targeted.[5]

In this paper, I develop a multisector New Keynesian dynamic stochastic general equilibrium (DSGE) model to assess in a structural approach whether exclusion of prices in certain categories in forming the price index for inflation targeting can be desirable in terms of welfare. Traditional arguments in defense of core inflation measures for inflation targeting usually involve that the prices excluded from core inflation measures tend to be more volatile and contain more transitory noises rather than signals of movements in underlying or trend inflation.[6] These arguments are often based on statistical properties of the prices being excluded from core inflation measures and mostly do not provide a structural explanation to why the particular excluded prices should be excluded. On the other hand, some studies (e.g., Aoki 2001, Mankiw and Reis 2003, Bodenstein et al. 2008) tried to provide theoretical or empirical evidence on the "why" question in terms of welfare in structural approaches. Findings of these studies generally supported the use of core inflation measures for inflation targeting.

A major finding of this paper is that the inflation rates in the sector of food and beverages purchased for off-premises consumption and the sector of housing and utilities are assigned large positive weights in the central bank's welfare-maximizing index of overall inflation, while the inflation rates in the other sectors are mostly assigned small-to-negligible or even negative weights. This finding suggests that the Fed should focus on prices in only a handful of categories when responding to inflation. Why these two sectors? A possible

[1] See, e.g., Hammond (2012).

[2] All inflation-targeting industrialized countries have adopted targets in the range of 1–3% according to Hammond (2012).

[3] The set of prices being excluded may be not fixed over time. For instance, the Federal Reserve Bank of Dallas calculates a trimmed mean personal consumption expenditures (PCE) inflation rate, in which the prices being excluded may vary from one period to another. See Dolmas (2005).

[4] Formally, it is the inflation rate implied by the price index for PCE excluding food and energy, which is composed by the US Bureau of Economic Analysis (BEA).

[5] See Mishkin (2007) and Wynne (2008).

[6] See, among others, Mishkin (2007), Wynne (2008), and Bullard (2011).

explanation is that price movements in these two sectors contain more signaling information on aggregate shocks, which is useful for the central bank to conduct monetary policy, than price movements in the other sectors do, largely because the sector-specific components of the price markup shocks in the two sectors have relatively small standard deviations. This result is consistent with Mankiw and Reis's (2003) finding that sectors with smaller-sized idiosyncratic shocks should receive larger weights in the central bank's optimal stability price index. It also supports the traditional "signal–noise" logic behind the use of core inflation for inflation targeting.

Interestingly, the central bank may optimally assign negative weights to the inflation rates in the sectors with the stickiest prices, which means that monetary policy actions in these sectors would be inflationary rather than disinflationary. Such unconventional policy actions may be motivated from the perspective of inflation stabilization. When prices in a sector are very sticky, they are unresponsive to monetary policy shocks and therefore may be exploited to tolerate some inflationary policy actions in exchange for more aggressive responses to the sectoral inflation rates that contain more information on aggregate shocks.

To accomplish the goal of this paper requires a multisector model that incorporates sectoral heterogeneities. Many recent New Keynesian DSGE models built for the US economy in the literature (e.g., Christiano et al. 2005, Smets and Wouters 2007) have been single-sector models abstracting from intricacies at the disaggregate level—such as heterogeneity in price stickiness across segments of the economy. However, heterogeneities exist in real-world economies,[7] and more importantly, their presence has implications for monetary policy analysis in New Keynesian models. For instance, a number of studies (e.g., Carvalho 2006, Dixon and Kara 2010, Nakamura and Steinsson 2010, Pasten et al. 2016) showed theoretically and/or empirically that monetary policy shocks tended to have larger and/or more persistent effects on aggregate inflation and/or on the real economy when heterogeneity in price stickiness was introduced.

Moreover, relative prices of goods usually play no first-order role in a typical single-sector model. Yet, Reis and Watson (2010) emphasized the quantitative importance of relative prices in accounting for variability of aggregate inflation and in generating the Phillips correlation between nominal inflation and the real variables. In addition, a number of studies demonstrated heterogenous responses of disaggregate prices and sectoral inflation rates to aggregate shocks, particularly monetary policy shocks (see e.g., Boivin et al. 2009, Nakajima et al. 2010, Baumeister et al. 2013), which would exert an important influence on relative prices (see e.g., Lastrapes 2006, Balke and Wynne 2007).

I extend the single-sector model by Smets and Wouters (2007) to incorporate sectoral heterogeneities, including differential sector sizes and sector-specific price stickiness, price

[7]Numerous studies (e.g., Bils and Klenow 2004, Klenow and Kryvtsov 2008, Nakamura and Steinsson 2008) have documented using micro data tremendous heterogeneity in the frequency of price change (i.e., price stickiness) across goods in the US economy. See, e.g., Altissimo et al. (2006) and Dhyne et al. (2006) for the euro area.

markups, degrees of price indexation, and idiosyncratic price markup shocks. A first-order role of relative prices arises in equilibrium inflation dynamics as a result of the introduction of sectoral heterogeneities. The multisector model also links fluctuations in sectoral real activities to movements in sectoral relative prices and shows that the sectors in which the price levels fall less are the sectors in which the output levels fall more in the face of a contractionary monetary policy shock. Boivin et al. (2009) estimated a factor-augmented vector autoregression (FAVAR) and found a negative cross-sectional relationship between the responses of PCE prices and those of PCE quantities to a contractionary monetary policy shock. The multisector model in this paper potentially provides a structural explanation to Boivin et al.'s aforementioned finding.

I estimate a 12-sector version of the model using Bayesian techniques with quarterly US data spanning the period of 1985Q1–2015Q4. Sectors are identified mostly by third-level disaggregate categories underlying PCE. The estimated model is generally capable of qualitatively explaining the cross-sectional difference in sectoral price stickiness evidenced by the micro data on frequency of price change collected by Bils and Klenow (2004). The estimates suggest that the Fed did not respond to changes in the prices of gasoline and other energy goods or changes in the price of health care over the sample period. On the other hand, the Fed seemed to target an index of overall inflation consisted of sectoral inflation rates in sectors other than the energy sector or the health care sector, weighted by sectoral consumption expenditure shares but with a relatively higher weight on the inflation rate in the sector of housing and utilities. Since the estimated weight of the inflation rate in the food sector is non-zero, the Fed did respond to changes in food price as opposed to what a central bank targeting core inflation excluding food and energy inflation would have done.

For welfare evaluation, I attempt to approximate welfare of the representative household via simulation. The welfare gains achieved by moving to targeting an optimal index of overall inflation turn out to be small, suggesting that the current inflation target adopted by the Fed is almost indistinguishable from the optimal one in terms of welfare. On the other hand, I find that more aggressive targeting of the output gap can offer much larger welfare gains.

This study is related to Aoki (2001), Mankiw and Reis (2003), and Bodenstein et al. (2008). The three studies all considered optimal monetary policy in economies with heterogenous sectors. This study, however, differs from the three aforementioned studies in several aspects. First, this study is based on a fully estimated structural model, while the three aforementioned studies were based on either non-estimated structural models or a (partially) estimated reduced-form model. Second, this study includes a total of twelve heterogenous sectors, while the three aforementioned studies included up to four heterogenous sectors. Third, no sector in this study has completely flexible prices, while the three aforementioned studies each included at least one sector with completely flexible prices. Forth, this study focuses on optimizing the composition of the index of overall inflation to be targeted by the central bank, while the three aforementioned studies considered optimal monetary policy in general.[8]

## 2 The Model Economy

The model in this paper is heavily based on the one by Smets and Wouters (2007), and the multisector setup is related to that by Carvalho and Lee (2011). The model economy comprises households, a labor packer, a final-composite-good producer, sectoral-composite-good producers, intermediate-good producers, a government, and a central bank. The model economy follows a balanced growth path, along which the growth rate is $\gamma > 1$. I assume that only the consumption-good market but not the labor or the capital market is segmented into $S$ sectors. In this section I describe the behavior of each participant in model economy, the market clearing conditions, and the resource constraint. Complete derivation of the equations characterizing the equilibrium and the log-linearized system is included in a separate appendix.[9]

### 2.1 Intermediate-good producers

Assume a continuum of intermediate-good producers indexed by $(s, j)$, where the first index $s = 1, \ldots, S$ identifies the sector and the second index $j \in (0, 1)$ identifies the particular producer.[10] The set $J_s$ collects the indices of the intermediate-good producers in sector $s$ and has a measure of $\omega_s$, which is the defined size of sector $s$. The index sets satisfy $\bigcup_{s=1}^{S} J_s = (0, 1)$ so that $\sum_{s=1}^{S} \omega_s = 1$.

In period $t$, intermediate-good producer $(s, j)$ $(s = 1, \ldots, S,\ j \in J_s)$ hires $L_t(s, j)$ units of composite labor through the labor market at the aggregate wage $W_t$ and rents $K_t^{\mathrm{f}}(s, j)$ units of capital from the households at the rental rate $R_t^k$ to produce a differentiated intermediate good $(s, j)$ using a labor-augmented Cobb–Douglas technology with a fixed cost:

$$Y_t(s, j) = \max\left\{\epsilon_t^a [K_t^{\mathrm{f}}(s, j)]^\alpha [\gamma^t L_t(s, j)]^{1-\alpha} - \gamma^t \Psi_s, 0\right\},$$

where $Y_t(s, j)$ is the quantity of intermediate good $(s, j)$ produced, $\epsilon_t^a > 0$ is an exogenous shock to the total factor productivity, $\alpha \in (0, 1)$ is the output elasticity of capital, and $\Psi_s > 0$

[8] Mankiw and Reis (2003) started from considering the optimal monetary policy but then focused on output gap stabilization.

[9] Available upon request.

[10] In fact a single index $j$ is sufficient to identify a particular intermediate-good producer and $s = s(j)$ can be a function of the index $j$. Nonetheless, I use $(s, j)$ to show explicitly the sector.

is a fixed cost.[11] The period-$t$ profit of intermediate-good producer $(s, j)$ is given by

$$\Delta_t^y(s, j) = P_t(s, j)Y_t(s, j) - W_t L_t(s, j) - R_t^k K_t^{\mathrm{f}}(s, j),$$

where $P_t(s, j)$ is the price of $Y_t(s, j)$.

Since the intermediate-good producers produce differentiated goods, they have monopolistic power in their respective product markets. The intermediate-good producers set prices à la Calvo (1983) but with partial indexation. Intermediate-good producer $(s, j)$ can re-optimize its price and set a new one $P_t^*(s, j)$ only when it receives a random signal of probability $1 - \theta_p(s) \in (0, 1)$; otherwise it adjusts its price according to the indexation rule

$$P_t(s, j) = P_{t-1}(s, j)\pi_{t-1}^{\iota_p(s)}\overline{\pi}^{1-\iota_p(s)},$$

where $\pi_{t-1} = P_{t-1}/P_{t-2}$ is the last period's inflation rate, $\overline{\pi}$ is the steady-state inflation rate, and $\iota_p(s) \in [0, 1]$ is the degree of dynamic price indexation in sector $s$. Let $D_t^p(s) = \pi_t^{\iota_p(s)}\overline{\pi}^{1-\iota_p(s)}$ so that the price indexation rule is $P_t(s) = P_{t-1}(s)D_{t-1}^p(s)$. Let $D_{t,t+\tau}^p(s) = \prod_{d=0}^{\tau} D_{t+d}^p(s)$.

When intermediate-good producer $(s, j)$ gets the opportunity to re-optimize its price, it chooses a new price $P_t^*(s, j)$ to maximize the expected discounted future profit in the case that $P_t^*(s, j)$ will remain effective forever, i.e.,

$$\max_{P_t^*(s,j)} \mathbb{E}_t \sum_{\tau=0}^{\infty} \theta_p(s)^\tau M_{t,t+\tau}(P_t^*(s, j)D_{t,t+\tau-1}^p(s) - \mathrm{MC}_{t+\tau})Y_{t+\tau|t}(s, j),$$

where $M_{t,t+\tau}$ is a stochastic discount factor and $\mathrm{MC}_{t+\tau}$ is the nominal marginal cost of production in period $t + \tau$,[12] subject to the demand schedule implied by sectoral output aggregation (to be described shortly), i.e.,

$$Y_{t+\tau|t}(s, j) = \frac{1}{\omega_s}\left(\frac{P_t^*(s, j)D_{t,t+\tau-1}^p(s)}{P_{t+\tau}(s)}\right)^{-(1+\epsilon_{t+\tau}^p(s))/\epsilon_{t+\tau}^p(s)} Y_{t+\tau}(s),$$

where $\epsilon_{t+\tau}^p(s) > 0$ is an exogenous shock to the sector-$s$ price markup in period $t + \tau$.

In any period, a proportion of $1 - \theta_p(s)$ of sector-$s$ intermediate-good producers reset their prices while the rest index their prices. Given the nature of the sectoral price aggregator

[11] I assume that the parameters $\Psi_s$, $s = 1, \ldots, S$, which are non-identifiable individually in subsequent estimation, are such that the production level of any intermediate-good producer is always positive in the neighborhood of the steady state. Nonetheless, the model is to be parameterized such that the aggregate production level being zero is (almost) impossible in the neighborhood of the steady state.

[12] It can be shown that the marginal cost of production is independent of the producer. See the appendix.

(to be described shortly), the law of motion of the sectoral price level $P_t(s)$ is given by

$$P_t(s) = \left[(1-\theta_p(s))\left(P_t^*(s)\right)^{-1/\epsilon_t^p(s)} + \theta_p(s)\left(P_{t-1}(s)D_{t-1}^p(s)\right)^{-1/\epsilon_t^p(s)}\right]^{-\epsilon_t^p(s)}.$$

### 2.2 Sectoral-composite-good producers

Assume in each sector a sectoral-composite-good producer who purchases $Y_t(s,j)$ units of intermediate good from intermediate-good producer $(s,j)$ at the price $P_t(s,j)$, produces $Y_t(s)$ units of sector-$s$ composite good, and then sells the composite good for the price $P_t(s)$ ($s=1,\dots,S$, $j \in J_s$). Taking $P_t(s)$ and $\{P_t(s,j)\}_{j\in J_s}$ as given, the sector-$s$ composite-good producer chooses $Y_t(s)$ and $\{Y_t(s,j)\}_{j\in J_s}$ in each period to maximize its profit

$$P_t(s)Y_t(s) - \int_{J_s} P_t(s,j)Y_t(s,j)\,\mathrm{d}j$$

subject to the constant elasticity of substitution (CES) aggregator

$$Y_t(s) = \omega_s^{-\epsilon_t^p(s)}\left[\int_{J_s} Y_t(s,j)^{1/(1+\epsilon_t^p(s))}\,\mathrm{d}j\right]^{1+\epsilon_t^p(s)}.$$

The implied demand for intermediate good $(s,j)$ given sectoral demand $Y_t(s)$ is

$$Y_t(s,j) = \omega_s^{-1}\left(\frac{P_t(s,j)}{P_t(s)}\right)^{-(1+\epsilon_t^p(s))/\epsilon_t^p(s)} Y_t(s),$$

and sectoral price aggregation is given by

$$P_t(s) = \left(\omega_s^{-1}\int_{J_s} P_t(s,j)^{-1/\epsilon_t^p(s)}\,\mathrm{d}j\right)^{-\epsilon_t^p(s)}.$$

### 2.3 The final-composite-good producer

Assume a final-composite-good producer who purchases $Y_t(s)$ units of sector-$s$ composite good at the price $P_t(s)$ ($s=1,\dots,S$) and produces $Y_t$ units of final composite good for the price $P_t$. $P_t$ is the period-$t$ aggregate price level. Taking $P_t$ and $\{P_t(s)\}_{s=1}^S$ as given, the final-composite-good producer chooses $Y_t$ and $\{Y_t(s)\}_{s=1}^S$ in each period to maximize its profit

$$P_tY_t - \sum_{s=1}^{S} P_t(s)Y_t(s)$$

subject to the CES aggregator

$$Y_t = \left( \sum_{s=1}^{S} \omega_s^{\nu} Y_t(s)^{1-\nu} \right)^{1/(1-\nu)},$$

where $\nu > 0$ is (the absolute value of) the inverse of the elasticity of substitution across sectoral composite goods. The implied demand for sector-$s$ composite good given aggregate demand $Y_t$ is

$$Y_t(s) = \omega_s \left( \frac{P_t(s)}{P_t} \right)^{-1/\nu} Y_t, \tag{1}$$

and implied price aggregation is given by

$$P_t = \left[ \sum_{s=1}^{S} \omega_s P_t(s)^{(\nu-1)/\nu} \right]^{\nu/(\nu-1)}. \tag{2}$$

Note that when $\nu \to 0$, the sectoral composite goods tend to become perfect substitutes of each other, which obscures the difference between sectors. As a result, the multisector model collapses to a single-sector one as $\nu \to 0$.

Define the sectoral relative prices

$$\varphi_t(s) = \frac{P_t(s)}{P_t}, \quad s = 1, \ldots, S,$$

and the sectoral inflation rates

$$\pi_t(s) = \frac{P_t(s)}{P_{t-1}(s)} = \frac{\varphi_t(s)}{\varphi_{t-1}(s)} \pi_t, \quad s = 1, \ldots, S. \tag{3}$$

### 2.4 Households

Assume a continuum of infinitely lived households indexed by $i \in (0, 1)$. In period $t$, household $i$ purchases final composite consumption good $C_t(i)$ at the price $P_t$, investment good $I_t(i)$ at the price $P_t$ to accumulate capital $K_{t+1}(i)$, and one-period discount bond $B_{t+1}(i)$ with the nominal interest rate $R_t$ and an exogenous stochastic risk premium $\epsilon_t^b > 0$. Households rent capital stock to intermediate-good producers, which households own. The effective amount of capital that household $i$ rents out in period $t$ is $K_t^{\mathrm{f}}(i) = Z_t(i)K_t(i)$, where $Z_t(i)$ is the level of capital utilization set by the household. Household $i$ earns $R_t^k Z_t(i)K_t(i)$ from capital rental and incurs a cost $P_t S_z(Z_t(i))K_t(i)$ in setting the utilization level, where $S_z(\cdot)$ is a cost function (described below). In addition, household $i$ supplies differentiated labor $L_t(i)$ at the wage $W_t^{\mathrm{h}}(i)$, earns $B_t(i)$ from last period's bond, and receives lump-sum transfer net of lump-sum tax $P_t T_t(i)$ from the government, profit $\Delta_t^y(i)$ from intermediate-good producers, and dividend $\Delta_t^l(i)$ from the labor packer.

Household $i$'s intertemporal budget constraint is given by

$$P_t C_t(i) + P_t I_t(i) + \frac{B_{t+1}(i)}{R_t/\epsilon_t^b} + P_t S_z(Z_t(i))K_t(i)$$
$$\leq W_t^{\mathrm{h}}(i)L_t(i) + R_t^k Z_t(i)K_t(i) + B_t(i) + P_t T_t(i) + \Delta_t^y(i) + \Delta_t^l(i).$$

The law of motion of household $i$'s capital stock is given by

$$K_{t+1}(i) = (1-\delta)K_t(i) + \epsilon_t^i \left(1 - S_i\left(\frac{I_t(i)}{I_{t-1}(i)}\right)\right) I_t(i),$$

where $\delta \in (0,1)$ is the depreciation rate, $\epsilon_t^i > 0$ is an exogenous shock to marginal efficiency of investment (MEI), and $S_i(\cdot)$ is an investment adjustment cost function (described below).

Given the initial bond holding $B_0(i)$, the initial capital stock $K_0(i)$, and pre-period-0 average consumption $\overline{C}_{-1}$ and taking $\{\overline{C}_t, P_t, R_t, W_t^{\mathrm{h}}(i), R_t^k, T_t(i), \Delta_t^y(i), \Delta_t^l(i)\}_{t=0}^{\infty}$ as given, household $i$ chooses $\{C_t(i), L_t(i), B_{t+1}, I_t(i), Z_t(i)\}_{t=0}^{\infty}$ to maximize the expected lifetime utility

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U_t(i)$$

subject to the intertemporal budget constraint and the law of motion of capital stock. The period utility function $U_t(i)$ defined as

$$U_t(i) = \frac{1}{1-\sigma_c}\left(C_t(i) - h\overline{C}_{t-1}\right)^{1-\sigma_c} \exp\left(-\frac{1-\sigma_c}{1+\sigma_l}\chi L_t(i)^{1+\sigma_l}\right),$$

where $\beta \in (0,1)$ is the subjective discount factor, $\sigma_c > 0$ is the inverse of the elasticity of intertemporal substitution (EIS) of consumption, $h \in (0,1)$ is a habit parameter, $\chi > 0$ measures the relative disutility of labor supply, and $\sigma_l > 0$ is the inverse of Frisch elasticity of labor supply.

The functional form of $S_z(\cdot)$ is[13]

$$S_z(Z) = \frac{\bar{r}^k}{\sigma^z}[\exp(\sigma^z(Z-1)) - 1],$$

such that $S_z(1) = 0$, $S_z'(1) = \bar{r}^k$ and $S_z''(1) = \bar{r}^k\sigma^z$, where $\bar{r}^k$ is the steady-state real rental rate of capital and $\sigma^z > 0$ is a curvature parameter. The functional form of $S_i(\cdot)$ is

$$S_i(x) = \frac{1}{2}\left[\exp\left(\sqrt{S_i''}(x-\bar{x})\right) + \exp\left(-\sqrt{S_i''}(x-\bar{x})\right)\right] - 1,$$

where $x = I_t(i)/I_{t-1}(i)$ and $\bar{x} = \gamma$ is the steady state of $x$, such that $S_i(\gamma) = S_i'(\gamma) = 0$

[13]The functional forms of $S_z(\cdot)$ and $S_i(\cdot)$ are borrowed from Christiano et al. (2014). The log-linearized system (derived in the appendix) and the equilibrium dynamics in the neighborhood of the steady state do not depend on particular functional forms but do depend on the curvature parameters $\sigma^z$ and $S_i''$.

and $S_i''(\gamma) = S_i''$, where $S_i'' > 0$ is a curvature parameter. For estimation purpose, I re-parameterize $\sigma^z$ and $S_i''$ as

$$\sigma^z = \frac{\kappa_z}{1-\kappa_z} \quad \text{and} \quad S_i'' = \frac{\kappa_i}{1-\kappa_i},$$

where $\kappa_z \in (0,1)$ and $\kappa_i \in (0,1)$ are two replacement parameters. It is shown in the appendix that, as $\kappa_z \to 1$, changing the level of capital utilization tends to be more costly, and thus the equilibrium level of capital utilization tends to remain constant; on the other hand, as $\kappa_z \to 0$, changing the level of capital utilization tends to be less costly, and the equilibrium capital rental rate, which is the marginal cost of setting the utilization level, tends to remain constant. Similarly, as $\kappa_i \to 1$, adjusting investment tends to be more costly, and thus the equilibrium level of investment tends to remain constant; on the other hand, as $\kappa_i \to 0$, adjusting investment tends to be less costly, and thus the equilibrium price of capital tends to remain constant.

### 2.5 The labor packer

Since the households supply differentiated labor, they have monopolistic power in the market of their own labor. Assume a labor packer that aggregates individual labor supplies and delegates negotiation of the wage rates.

The labor packer uses a CES aggregator to form composite labor $L_t$ from differentiated labor $\{L_t(i)\}_{i\in(0,1)}$ supplied by the households:

$$L_t = \left[\int_0^1 L_t(i)^{1/(1+\epsilon_t^w)}\ \mathrm{d}i\right]^{1+\epsilon_t^w}, \tag{4}$$

where $\epsilon_t^w > 0$ is an exogenous shock to the period-$t$ wage markup. The labor packer then sells composite labor to intermediate-good producers in a perfectly competitive market. Given aggregate labor demand $L_t$, the demand for household $i$'s labor is determined by

$$L_t(i) = \left(\frac{W_t(i)}{W_t}\right)^{-(1+\epsilon_t^w)/\epsilon_t^w} L_t, \tag{5}$$

where $W_t(i)$ is the market wage rate for household $i$'s labor and $W_t$ is the aggregate wage rate given by

$$W_t = \left(\int_0^1 W_t(i)^{-1/\epsilon_t^w}\ \mathrm{d}i\right)^{-\epsilon_t^w}. \tag{6}$$

The labor packer sets wages in a way analogous to the intermediate-good producers setting their prices. Specifically, the labor packer can re-optimize and set a new wage $W_t^*(i)$ for household $i$'s labor only when it receives a random signal of probability $1-\theta_w \in (0,1)$;

otherwise it adjusts the wage according to the indexation rule

$$W_t(i) = W_{t-1}(i)\gamma\pi_{t-1}^{\iota_w}\overline{\pi}^{1-\iota_w},$$

where $\iota_w \in [0,1]$ is the degree of dynamic wage indexation. Let $D_t^w = \gamma\pi_t^{\iota_w}\overline{\pi}^{1-\iota_w}$ so that the wage indexation rule is $W_t = W_{t-1}D_{t-1}^w$. Let $D_{t,t+\tau}^w = \prod_{d=0}^{\tau} D_{t+d}^w$.

When the labor packer gets the opportunity to re-optimize household $i$'s wage, it chooses a new wage $W_t^*(i)$ to maximize household $i$'s expected future utility in the case that the new wage will remain effective forever, i.e.,

$$\max_{W_t^*(i)} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\theta_w)^\tau U_{t+\tau|t}(i),$$

where the subscript "$t+\tau|t$" indicates a variable in period $t+\tau$ conditional on that the wage rate was last re-optimized in period $t$, subject to the intertemporal budget constraint

$$\begin{aligned} &P_{t+\tau}C_{t+\tau|t}(i) + P_{t+\tau}I_{t+\tau|t}(i) + \frac{B_{t+\tau+1|t}(i)}{R_{t+\tau}/\epsilon_{t+\tau}^b} + P_{t+\tau}S_z(Z_{t+\tau|t}(i))K_{t+\tau|t}(i) \\ &\leq W_t^*(i)D_{t,t+\tau-1}^w L_{t+\tau|t}(i) + R_{t+\tau}^k Z_{t+\tau|t}(i)K_{t+\tau|t}(i) + B_{t+\tau|t}(i) + P_{t+\tau}T_{t+\tau}(i) + \Delta_{t+\tau}^y(i), \\ &\qquad \tau = 0,1,2,\ldots, \end{aligned}$$

and the labor demand schedule implied by (5), i.e.,

$$L_{t+\tau|t}(i) = \left(\frac{W_t^*(i)D_{t,t+\tau-1}^w}{W_{t+\tau}}\right)^{-(1+\epsilon_{t+\tau}^w)/\epsilon_{t+\tau}^w} L_{t+\tau}.$$

In any period, the labor packer resets the wages of a proportion of $1-\theta_w$ of the households and at the same time indexes the wages of the remaining households. Given the nature of the wage aggregator (6), the law of motion of the aggregate wage $W_t$ is given by

$$W_t = \left[(1-\theta_w)\left(W_t^*\right)^{-1/\epsilon_t^w} + \theta_w\left(W_{t-1}D_{t-1}^w\right)^{-1/\epsilon_t^w}\right]^{-\epsilon_t^w}.$$

### 2.6 The government

In period $t$, the government purchases final composite consumption good $G_t$ at the price $P_t$ for exogenous spending, pays $B_t$ for the bonds issued in the last period, transfers $T_t$ (net of taxes) to the households, and issues new discount bonds $B_{t+1}/(R_t/\epsilon_t^b)$. Here $B_t = \int_0^1 B_t(i)\,\mathrm{d}i$ is the aggregate bond holding and $T_t = \int_0^1 T_t(i)\,\mathrm{d}i$ is the aggregate transfer. The intertemporal budget constraint of the government is

$$P_tG_t + B_t + P_tT_t = \frac{B_{t+1}}{R_t/\epsilon_t^b},$$

with $B_0$ given. I assume

$$\epsilon_t^g = G_t/\gamma^t > 0$$

to be the exogenous government spending shock.

## 2.7 The central bank

The central bank responds to inflation and the output gap, which is the difference between the actual output and the natural (or the potential) output. The natural output is defined as the level of output in the economy with flexible wage and prices ($\theta_w = \theta_p(s) = 0$, for all $s = 1, \dots, S$) and with the wage and the price markup shocks shut down ($\epsilon_t^w = \bar{\epsilon}^w$ and $\epsilon_t^p(s) = \bar{\epsilon}^p(s)$, for all $s = 1, \dots, S$ and $t = 0, 1, 2, \dots$). The central bank uses the interest rate as the policy instrument. Since there are multiple sectors and thus multiple inflation rates including the aggregate inflation rate and $S$ sectoral inflation rates, the central bank's policy can vary as selection of the inflation rates to which the central bank responds varies or as the strength of responses varies. I consider a single-inflation-target scheme in which the central bank chooses to respond to the aggregate inflation rate and a multi-inflation-target scheme in which the central bank chooses to respond to individual sectoral inflation rates.

For convenience I specify the monetary policy schemes in log-linearized forms. Let $\hat{x}_t = (x_t - \bar{x})/\bar{x} \approx \ln(x_t/\bar{x})$ denote the relative deviation of the variable $x_t$ from its steady sate $\bar{x}$, which is approximately the logarithmic deviation. Under the single-inflation-target scheme, the central bank follows a generalized Taylor (1993) rule:

$$\hat{R}_t = \rho_r \hat{R}_{t-1} + (1 - \rho_r)\left[\rho_\pi \hat{\pi}_t + \rho_x(\hat{y}_t - \hat{y}_t^{\text{n}})\right] + \hat{\epsilon}_t^r, \tag{7}$$

where $\hat{y}_t^{\text{n}}$ is the (log deviation of detrended) natural output, $\rho_r \in (0, 1)$ is a policy smoothing parameter, $\rho_\pi > 1$ measures the strength of the central bank's response to aggregate inflation, $\rho_x > 0$ measures the strength of the central bank's response to the aggregate output gap, and $\epsilon_t^r > 0$ is an exogenous monetary policy shock.

Under the multi-inflation-target scheme, the central bank follows

$$\hat{R}_t = \rho_r \hat{R}_{t-1} + (1 - \rho_r)\left[\sum_{s=1}^{S} \rho_\pi(s)\hat{\pi}_t(s) + \rho_x(\hat{y}_t - \hat{y}_t^{\text{n}})\right] + \hat{\epsilon}_t^r, \tag{8}$$

where $\rho_\pi(s)$ ($s = 1, \dots, S$) is the strength of the central bank's response to sector-$s$ inflation. Scheme (8) is a relaxation of scheme (7). The term $\sum_{s=1}^{S} \rho_\pi(s)\hat{\pi}_t(s)$ in the bracket in (8) can be re-parameterized as

$$\rho_\pi^* \sum_{s=1}^{S} (1 + \rho_\pi^{**}(s))\omega_s^* \hat{\pi}_t(s), \tag{9}$$

where $\rho_\pi^* > 1$,

$$\sum_{s=1}^{S}(1+\rho_\pi^{**}(s))\omega_s^* = 1, \tag{10}$$

and $\omega_s^* = \omega_s \overline{\varphi}(s)^{(\nu-1)/\nu}$ such that $\sum_{s=1}^{S}\omega_s^* = 1$ (following from (2)). Let

$$\rho_\pi^*(s) = (1+\rho_\pi^{**}(s))\omega_s^*, \quad s = 1, \dots, S.$$

Since $\hat{\pi}_t(s) = \sum_{s=1}^{S}\omega_s^*\hat{\pi}_t(s)$, $\{\omega_s^*\}_{s=1}^{S}$ can be interpreted as the "natural" weights of sectoral inflation rates $\{\hat{\pi}_t(s)\}_{s=1}^{S}$ in the aggregate inflation rate $\hat{\pi}_t$. Thus, the multi-inflation-target scheme can also be motivated by that the central bank is composing an index of overall inflation with weights on sectoral inflation rates possibly different than the natural ones that arise when targeting the aggregate inflation rate. With re-parameterization (9), $\rho_\pi^*$ can be interpreted as the strength of the central bank's overall response to target inflation, while $\{\rho_\pi^*(s) = (1+\rho_\pi^{**}(s))\omega_s^*\}_{s=1}^{S}$ can be interpreted as the sectoral weights, and $\rho_\pi^{**}(s) > 0$ ($\rho_\pi^{**}(s) < 0$; $s = 1, \dots, S$) indicates that the weight on sector-$s$ inflation $\hat{\pi}_t(s)$ in the central bank's target inflation index is more (less) than its natural weight.

Denote the model equipped with the single-inflation-target scheme by $\mathscr{M}_1$ and the model equipped with the multi-inflation-target scheme by $\mathscr{M}_2$.

### 2.8 Market clearing and the resource constraint

The economy-wide aggregate labor demand is the sum of sectoral labor demands and meets the aggregate labor supply defined in (4):

$$L_t = \sum_{s=1}^{S} L_t(s) = \sum_{s=1}^{S}\int_{J_s} L_t(s(j), j)\, \mathrm{d}j = \int_0^1 L_t(s(j), j)\, \mathrm{d}j,$$

where $L_t$, $L_t(s)$, and $L_t(s,j)$ ($s = 1, \dots, S$, $j \in (0,1)$) are all in units of composite labor. The economy-wide aggregate capital demand is the sum of capital rented by intermediate-good producers in all sectors and meets the aggregate capital stock that is accumulated by the households and available for rental:

$$K_t^{\mathrm{f}} = \sum_{s=1}^{S} K_t^{\mathrm{f}}(s) = \sum_{s=1}^{S}\int_{J_s} K_t^{\mathrm{f}}(s,j)\, \mathrm{d}j = \int_0^1 K_t^{\mathrm{f}}(s(j), j)\, \mathrm{d}j = \int_0^1 K_t^{\mathrm{f}}(i)\, \mathrm{d}i.$$

The government clears the bond market. Clearing of the consumption-good markets requires that for each good produced in the economy the quantity supplied equals the sum of the quantities demanded for consumption, investment, setting the level of capital utilization, and government spending. The economy's resource constraint is given by

$$C_t + I_t + S_z(Z_t)K_t + G_t = Y_t.$$

### 2.9 Exogenous shocks

A total of seven types of exogenous shocks are included in the model economy: a risk premium shock $\epsilon_t^b$; a shock to MEI $\epsilon_t^i$; a technology shock $\epsilon_t^a$; sectoral price markup shocks $\epsilon_t^p(s)$, $s = 1, \ldots, S$; a wage markup shock $\epsilon_t^w$; a government spending shock $\epsilon_t^g$; and a monetary policy shock $\epsilon_t^r$. For estimation purpose I scale some of the shocks (see the appendix for more detail).[14] The symbols for scaled shocks, innovations, and variance (or standard deviation) parameters each have on them a tilde (˜) accent. The stochastic processes of the exogenous shocks are specified in log-linearized forms in what follows.

The scaled risk premium shock $\tilde{\epsilon}_t^b$ follows a first-order autoregression (AR(1)) with a normally and independently distributed (NID) innovation:

$$\tilde{\epsilon}_t^b = \rho_b \tilde{\epsilon}_{t-1}^b + \tilde{\eta}_t^b, \quad \tilde{\eta}_t^b \sim \text{NID}(0, \tilde{\sigma}_b^2),$$

where $\rho_b$ is the AR(1) coefficient measuring persistence of the shock and $\tilde{\eta}_t^b$ is the innovation with a zero mean and a variance of $\tilde{\sigma}_b^2$. Similarly, the scaled MEI shock $\tilde{\epsilon}_t^i$, the technology shock $\hat{\epsilon}_t^a$, and the scaled wage markup shock $\tilde{\epsilon}_t^w$ follow AR(1) processes with NID innovations, in which $\rho_i$, $\rho_a$, and $\rho_w$ are the respective AR(1) coefficients measuring persistence of the respective shocks and $\tilde{\sigma}_i^2$, $\sigma_a^2$, and $\tilde{\sigma}_w^2$ are the variances of the respective underlying NID innovations.

The sector-$s$ ($s = 1, \ldots, S$) price markup shock $\hat{\epsilon}_t^p(s)$ has two components: a common component $\hat{\zeta}_t^p$ and a sector-specific component $\hat{\zeta}_t^p(s)$ such that

$$\hat{\epsilon}_t^p(s) = \hat{\zeta}_t^p + \hat{\zeta}_t^p(s). \tag{11}$$

$\hat{\zeta}_t^p$ and $\hat{\zeta}_t^p(s)$ follow AR(1) processes with persistence $\rho_p$ and $\rho_p(s)$, respectively. The NID innovations underlying $\hat{\zeta}_t^p$ and $\hat{\zeta}_t^p(s)$ are $\eta_t^p$ and $\eta_t^p(s)$ with variances $\sigma_p^2$ and $\sigma_p^2(s)$, respectively. The scaled version of (11) to be used in estimation is:

$$\tilde{\epsilon}_t^p(s) = \frac{(1 - \beta\gamma^{1-\sigma_c}\theta_p(s))(1 - \theta_p(s))}{\theta_p(s)} \zeta^p \tilde{\zeta}_t^p + \tilde{\zeta}_t^p(s),$$

where $\tilde{\zeta}_t^p$ and $\tilde{\zeta}_t^p(s)$ are scaled versions of $\hat{\zeta}_t^p$ and $\hat{\zeta}_t^p(s)$, respectively, and $\zeta^p$ is a scaling parameter. The variances of the scaled innovations underlying $\tilde{\zeta}_t^p$ and $\tilde{\zeta}_t^p(s)$ are $\tilde{\sigma}_p^2$ and $\tilde{\sigma}_p^2(s)$, respectively. The presence of a common component causes the sectoral price markup shocks to be contemporaneously correlated.

Following Smets and Wouters (2007), I assume that the government spending shock

[14] The standard deviations of the unscaled shocks can be quite disperse, which may pose difficulty in specifying suitable priors and lead to inefficiency in sampling the posterior distribution. The scaled shocks mostly have standard deviations of similar magnitude.

follows an augmented AR(1) process:

$$\hat{\epsilon}_t^g = \rho_g \hat{\epsilon}_{t-1}^g + \eta_t^g + \rho_{ga}\eta_t^a, \quad \eta_t^g \sim \text{NID}(0, \sigma_g^2),$$

where $\rho_g$ is the persistence parameter, $\eta_t^a$ is the innovation in the AR(1) process of the technology shock, and $\rho_{ga}$ is a parameter measuring the contribution of the technology innovation to the government spending shock. The monetary policy shock is simply an NID innovation:

$$\hat{\epsilon}_t^r = \eta_t^r, \quad \eta_t^r \sim \text{NID}(0, \sigma_r^2).$$

The total number of structural innovations in the model is $7 + S$.

## 3 The Aggregate New Keynesian Phillips curve and the Role of Relative Prices

By log-linearizing the intermediate-good producers' optimality conditions around the symmetric steady state, combining the resulting equations with the log-linearized equations of the law of motion of sectoral price levels, and then aggregating the resulting sectoral equations, I obtain the aggregate NKPC:

$$\begin{aligned}
\hat{\pi}_t = & \sum_{s=1}^{S} \omega_s^* \frac{\iota_p(s)}{1+\beta\gamma^{1-\sigma_c}\iota_p(s)} \hat{\pi}_{t-1} + \sum_{s=1}^{S} \omega_s^* \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\gamma^{1-\sigma_c}\iota_p(s)} \mathbb{E}_t\, \hat{\pi}_{t+1} \\
& + \sum_{s=1}^{S} \omega_s^* \frac{1-\beta\gamma^{1-\sigma_c}\theta_p(s)}{1+\beta\gamma^{1-\sigma_c}\iota_p(s)} \frac{1-\theta_p(s)}{\theta_p(s)} \left(\widehat{\text{mc}}_t + \overline{\sigma}^p(s)\hat{\epsilon}_t^p(s)\right) \\
& - \sum_{s=1}^{S} \omega_s^* \left( \frac{1+\beta\gamma^{1-\sigma_c}\theta_p^2(s)}{1+\beta\gamma^{1-\sigma_c}\iota_p(s)} \frac{1}{\theta_p(s)} \hat{\varphi}_t(s) - \frac{\hat{\varphi}_{t-1}(s) + \beta\gamma^{1-\sigma_c}\,\mathbb{E}_t\,\hat{\varphi}_{t+1}(s)}{1+\beta\gamma^{1-\sigma_c}\iota_p(s)} \right),
\end{aligned} \tag{12}$$

where $\overline{\sigma}^p(s) = \bar{\epsilon}^p(s)/(1+\bar{\epsilon}^p(s))$, $s = 1, \ldots, S$, and $\widehat{\text{mc}}_t$ is the (log deviation of) real marginal cost. As the NKPC in a typical single-sector model (with price indexation) does, (12) states that current aggregate inflation ($\hat{\pi}_t$) depends positively on past aggregate inflation ($\hat{\pi}_{t-1}$), expected future aggregate inflation ($\mathbb{E}_t\, \hat{\pi}_{t+1}$), the current real marginal cost ($\widehat{\text{mc}}_t$), and the current price markup shocks ($\{\hat{\epsilon}_t^p(s)\}_{s=1}^S$). A novel feature of the aggregate NKPC in the multisector model is that relative prices ($\{\hat{\varphi}_t(s)\}_{s=1}^S$) play a first-order role. The net effects of relative prices on aggregate inflation (i.e., the third line of (12)) do not vanish in general unless the sectors are homogenous in price stickiness and price indexation, i.e., $\theta_p(s) = \theta_p$ and $\iota_p(s) = \iota_p$, for all $s = 1, \ldots, S$.

In a typical single-sector model, despite the presence of price dispersion in the equilibrium due to asynchronous price resetting across intermediate-good producers, there is no first-order role of relative prices, which can be attributed to two factors. First, all intermediate-good producers choose the same price in the symmetric steady state at a single markup over the same nominal marginal cost. Therefore, log-linearization of the optimality conditions of the intermediate-good producers in the neighborhood of the steady state, which is a first-order approximation, cannot capture equilibrium price dispersion, which is a second-order feature. Second, although intermediate-good producers reset their prices at random time, there is a dichotomy in intermediate-good producers' price-setting behaviors at any given time: either re-optimizing or indexing prices. Additionally, all those who re-optimize their prices choose exactly the same new price, because across producers the marginal cost of production is the same and the current and the expected future price markups are the same; all those who index their prices follow exactly the same indexation rule. As a result, asynchrony of price changes or price dispersion does not manifest itself in the law of motion of the aggregate price level. Both factors suggest that the absence of a first-order role of relative prices in a single-sector model is ultimately due to that monopolistic intermediate-good producers are not sufficiently distinguished from each other in terms of their price-setting behaviors in a single-sector model.

In the multisector model considered here, the introduced sectoral heterogeneities further distinguish intermediate-good producers from each other. Intermediate-good producers in different sectors may impose different steady-state price markups and thus choose different prices in the steady state.[15] In addition, the law of motion of the sectoral price level varies across sectors, because the proportion of producers resetting their prices ($1 - \theta_p(s)$) varies, the new price set by re-optimizing producers varies due to sector-specific markup shocks ($\epsilon_t^p(s)$), and the degree of price indexation ($\iota_p(s)$) varies. Consequently, relative prices arise in the aggregate NKPC in the multisector model.

Relative prices provide the link between sectoral-level aggregates and economy-wide aggregates in the multisector model as well. Log-linearizing (1) (after detrending it) gives

$$\hat{y}_t(s) = -\hat{\varphi}_t(s)/\nu + \hat{y}_t, \tag{13}$$

which states that sectoral output ($\hat{y}_t(s)$) is economy-wide aggregate output ($\hat{y}_t$) less a relative price term ($\hat{\varphi}_t(s)/\nu$).[16] Suppose the model economy is hit by a contractionary shock that causes output and the price level to fall (e.g., an unexpected increase in the nominal interest rate by the central bank). Then (13) suggests that the sectors in which the relative-price responses are positive, i.e., the sectors in which the sectoral price levels fall less than the economy-wide average price level does, will have relatively larger declines in output, and vice versa. This result potentially provides a structural explanation to Boivin et al.'s (2009) finding of a negative cross-sectional relationship between the responses of PCE prices and

[15]In subsequent estimation I calibrate steady-state price markups in all sectors to be the same, i.e., $\bar{\epsilon}^p(s) = \epsilon^p$, $s = 1, \dots, S$. Such calibration, however, does not eliminate the first-order role of relative prices in the NKPC, which persists as long as other sectoral heterogeneities exist, or alter how sectoral output and inflation depend on relative prices (to be discussed shortly), which persists as long as sectoral composite goods are not perfect substitutes of each other nor perfectly distinct from each other.

[16]Other authors (e.g., Aoki 2001, Bodenstein et al. 2008, Pasten et al. 2016) have obtained similar equations.

those of PCE quantities after a contractionary monetary policy shock in their estimated FAVAR.

Equation 14 has implications on how price stickiness in a sector affects movements in real variables in the sector relative to those in other sectors. In a sector with relatively more flexible prices, a larger proportion of producers in the sector are able to timely change their prices in the face of an aggregate shock. Hence the sectoral price level may jump by more than the economy-wide average price level does, and thus sectoral output may be shifted by less than economy-wide output is done according to (13). In other words, price flexibility acts as a shock absorber that trades nominal variability for real stability on the sectoral level. Some studies did find empirically a positive cross-sectional relationship between the speed or the magnitude of the response of the sectoral price to an aggregate shock and sectoral price flexibility (see, e.g., Maćkowiak et al. 2009, Kaufmann and Lein 2013, Bouakez et al. 2014), and a negative cross-sectional relationship between the magnitude of the responses of sectoral output and sectoral price flexibility (see Bouakez et al. 2014).

Additionally, (13) suggests that, other things equal, the more differentiated the sectoral composite goods are (a higher $\nu$), the less disperse the responses of sectoral output to a shock are across sectors. In the extreme that the sectoral composite goods are perfectly distinct and no substitution occurs ($\nu \to \infty$), dispersion in sectoral output movements across sectors is completely suppressed ($\hat{y}_t(s) = \hat{y}_t$, for all $s = 1, \dots, S$).

Log-linearizing (3) gives

$$\hat{\pi}_t(s) = \hat{\varphi}_t(s) - \hat{\varphi}_{t-1}(s) + \hat{\pi}_t, \tag{14}$$

which states that sectoral inflation ($\hat{\pi}_t(s)$) is economy-wide aggregate inflation ($\hat{\pi}_t$) plus a relative price term ($\Delta\hat{\varphi}_t(s) = \hat{\varphi}_t(s) - \hat{\varphi}_{t-1}(s)$). Equation 14 suggests that the *relatively* more inflationary sectors are those in which the relative prices grow faster.

## 4 Bayesian Estimation and Inference

The multisector models $\mathscr{M}_1$ and $\mathscr{M}_2$ are estimated with Bayesian techniques. In this section I first describe the data used in estimation and the measurement equations linking the variables in the model to the observed time series. Then I describe calibration of some of the model parameters and the priors for the estimated parameters. Finally I present and discuss the results of estimation at length.

### 4.1 Data

I use seven types of quarterly time series spanning 1985Q1–2015Q4 in estimation, including real output per capita ($y_t^{\text{data}}$), real consumption per capita ($c_t^{\text{data}}$), real investment per capita ($i_t^{\text{data}}$), labor supply per capita ($L_t^{\text{data}}$), the real wage ($w_t^{\text{data}}$), the nominal interest rate ($R_t^{\text{data}}$), and th aggregate and the sectoral inflation rates ($\pi_t^{\text{data}}$ and $\pi_t^{\text{data}}(s)$, $s = 1, \ldots, S$).[17]

The nominal interest rate in 1985Q1–2009Q1 is the daily effective federal funds rate in the last business day of the preceding quarter.[18] The nominal interest rate in 2009Q2–2015Q4 is the monthly Wu–Xia (2016) shadow federal funds rate in the last month of the preceding quarter, estimated by the Board of Governors of the Federal Reserve System.[19] The substitution of Wu–Xia shadow federal funds rate after 2008 is motivated by that, when the regular federal funds rate was at the zero lower bound from the end of 2008 to the end of 2015, it cannot capture the actual liquidity in the economy while Wu–Xia shadow federal funds rate contained economically meaningful information (Wu and Xia 2016).

The consumption-good market in the model economy is segmented. I identify sectors of the consumption-good market mostly by third-level disaggregate categories underlying PCE in Table 2.3.5 of the National Income and Product Accounts published by the US Bureau of Economic Analysis (BEA), excluding those for durable goods, which gives $S = 12$ sectors. Table 1 lists the sectors and their average consumption shares ($\omega_s^{\text{ob}}$, $s = 1, \ldots, S$). These shares are computed as the proportions of sectoral PCE in the total PCE on all nondurable goods and services, averaged over the sample period of 1985Q1–2015Q4. Table 1 shows that the majority (73%) of households' consumption expenditures were on services over the sample period, with the first largest category being housing and utilities[20] (sector 5) and the second largest category being health care (sector 6).

[Table 1 about here.]

Aggregate inflation is the first difference of the logarithm of a price index measuring the overall price level for PCE on nondurable goods and services. This price index is constructed as the ratio of the sum of nominal PCE on nondurable goods and services to the sum of real PCE in the two broad categories. Sectoral inflation is the first difference of the logarithm of the PCE price index in the sector. The last two columns of Table 1 show the inflation profiles of the twelve sectors. Over the sample period, sector 6 (health care) experienced the highest average inflation rate, while sector 2 (clothing and footwear) and sector 12

[17]Real output is obtained by deflating the nominal gross domestic product (GDP) by its implicit price deflator. Real consumption is the sum of real PCE on nondurables and services, each obtained by deflating the nominal series by the respective implicit price deflators. Real investment is the sum of real gross private domestic investment and real PCE on durables, each obtained by deflating the nominal series by the respective implicit price deflators. Labor supply is an index of hours worked of all persons in nonfarm business. The preceding time series are put in per capita terms before they enter the measurement equations by dividing them by the civilian non-institutional population aged 16 or over. The real wage is an index of per hour compensation in nonfarm business deflated by the implicit GDP deflator.

[18]This choice is to match the frequency of Wu–Xia shadow federal funds rate used in subsequent periods; see footnote 19. When the daily rate in the last business day of a given quarter is not available, the daily rate in the preceding business day is substituted. Such a time series of interest rate approximates the policy interest rate set by the central bank in the economy in the beginning of a period (a quarter).

[19]The estimated shadow rates are for the last business day of each month.

[20]Expenditures on housing dominate those on utilities, with the former taking up more than 83% of the sum of the two expenditures on average over the sample period.

(final consumption expenditures of nonprofit institutions serving households (NPISHs)) experienced the lowest, in fact negative, average inflation rates. The inflation rate in sector 3 (gasoline and other energy goods) was the most volatile, while that in sector 9 (food services and accommodations) was the least volatile. Details on the data, their sources, and the transformations applied are included in the appendix.

### 4.2 Measurement equations

Before presenting the measurement equations, I define the observable variables in the model. The model's observable (detrended) aggregate output $y_t^{\text{ob}}$ is linear aggregation of the (detrended) outputs of individual intermediate-good producers $\{y_t(s(j), j)\}_{j \in (0,1)}$:

$$y_t^{\text{ob}} = \int_0^1 y_t(s(j), j) \, \mathrm{d}j.$$

With subsequent calibration of the model, it can be shown that $\hat{y}_t^{\text{ob}} = \hat{y}_t$ (see the appendix). For the observable aggregate consumption, investment, and labor supply, similar relationships can be established. For prices and wages, I assume that the observable aggregates are identical to the ones aggregated with CES aggregators.[21]

The sector sizes $\{\omega_s\}_{s=1}^S$, as measured by the masses of intermediate-good producers in the sectors, are not observable. With subsequent calibration of the model, however, the unobservable sector size $\omega_s$ ($s = 1, \ldots, S$) coincides with the observable sector size $\omega_s^{\text{ob}}$, which is the sectoral consumption share listed in Table 1 (see the appendix for more detail).

The measurement equations are given by

$$\begin{aligned} &100 \cdot \big[\mathrm{d}\Delta \ln y_t^{\text{data}}, \mathrm{d}\Delta \ln c_t^{\text{data}}, \mathrm{d}\Delta \ln i_t^{\text{data}}, \mathrm{d}\Delta \ln L_t^{\text{data}}, \mathrm{d}\Delta \ln w_t^{\text{data}}, \\ &\qquad \mathrm{d}\Delta R_t^{\text{data}}/100, \mathrm{d}\pi_t^{\text{data}}, \mathrm{d}\pi_t^{\text{data}}(1), \ldots, \mathrm{d}\pi_t^{\text{data}}(S)\big]' \\ &= \big[\Delta \hat{y}_t, \Delta \hat{c}_t, \Delta \hat{i}_t, \Delta \hat{L}_t, \Delta \hat{w}_t, \Delta \hat{R}_t, \hat{\pi}_t, \hat{\pi}_t(1), \ldots, \hat{\pi}_t(S)\big]' + \boldsymbol{\eta}_t^{\text{me}}, \end{aligned}$$

where $\Delta$ is the first difference operator (i.e., $\Delta x_t = x_t - x_{t-1}$), d indicates removal of sample mean (i.e., $\mathrm{d}x_t = x_t - \sum_{t=1}^T x_t / T$), and $\boldsymbol{\eta}_t^{\text{me}}$ is an $(S+7)$-by-1 vector of measurement errors. I first difference the logarithm of per capita labor supply ($\ln L_t^{\text{data}}$) and the nominal interest rate ($R_t^{\text{data}}$) because univariate unit-root tests provide evidence in favor of presence of a unit root in the former series and to a less extent in the latter one.[22] Following Christiano et al.

[21] The real-world price or wage indices published by statistical agencies such as the BEA are generally not linear aggregation of individual prices or wages, which renders defining the observable aggregate price or wage in the model with a linear aggregator inappropriate. On the other hand, an aggregator mimicking what statistical agencies do to produce the published price or wage indices would complicate estimation of the model. My choices here are largely for simplicity.

[22] I applied multiple univariate unit-root tests on each series. For the logarithm of per capita labor supply ($\ln L_t^{\text{data}}$), all the tests favored presence of a unit root at any conventional significance level. For the nominal interest rate ($R_t^{\text{data}}$), the results were mixed and depended on the test method, lag order selection, and sample selection. See the appendix for details.

(2011) and Christiano et al. (2014), I remove the sample mean from each time series used in estimation.

Measurement errors are added for several reasons. First, the data are possibly measured with noise. A measurement error on the interest rate is warranted by the fact that the data in 2009Q2–2015Q4 are substituted with estimated shadow rates. Second, since in the model $\hat{\pi}_t = \sum_{s=1}^{S} \omega_s^* \hat{\pi}_t(s)$ but in the data $\mathrm{d}\pi_t^{\text{data}} \neq \sum_{s=1}^{S} \omega_s^* \cdot \mathrm{d}\pi_t^{\text{data}}(s)$ in general, the inclusion of the aggregate inflation rate and all the sectoral inflation rates as the observable variables at the same time would lead to stochastic singularity unless one or more measurement errors are added on the inflation rates. Third, measurement errors may help accommodate model misspecifications (Del Negro and Schorfheide 2009).

### 4.3 Calibration

[Table 2 about here.]

The calibrated parameters are listed in Table 2. The (quarterly) growth rate along the balanced growth path in the economy is set to $\gamma = 1.0046$, which implies an annual growth rate of real gross domestic product (GDP) per capita of about 1.9% and matches the average in the data over the period of 1985Q1–2008Q2.[23] The steady-state (quarterly) inflation rate is set to $\overline{\pi} = 1.0062$, implying an annual rate of 2.5%. The steady-state share of government spending in GDP is set to $\overline{g} = 0.17$, which matches the average in the subsample till 2008Q2.[24]

The inverse of the EIS is set to $\sigma_c = 1.25$, which is broadly consistent with micro and macro evidence.[25] The households' (quarterly) discount factor is calibrated at $\beta = 1/1.0013 \approx 0.9987$ so that the implied steady-state annual nominal interest rate is 5.43%, which matches the average in the subsample till 2008Q2. The equilibrium dynamics are independent of the parameter value of steady-state labor supply $\overline{L}$; however, I arbitrarily set $\overline{L} = 1$. The inverse of Frisch elasticity of labor supply is set to $\sigma_l = 2$. The (quarterly) depreciation rate of capital is set to $\delta = 0.025$. The exponent of capital in the production function is set to $\alpha = 0.33$. The calibrated values of $\sigma_l$, $\delta$, and $\alpha$ are commonly used in the literature. The parameter $\psi = \sum_{s=1}^{S} \omega_s \Psi_s / \overline{y}$, which is the ratio of the weighted average sectoral fix cost to steady-state output, is set to $\psi = 0.04$.

I fix the steady-state wage markup at 5%, i.e., $\bar{\epsilon}^w = 0.05$, and the steady-state price markups in all sectors at 20%, i.e., $\bar{\epsilon}^p(s) = 0.2$, for all $s = 1, \ldots, S$. These values were used

[23] I use the subsample over 1985Q1–2008Q2 to calibrate some of the parameters because data in subsequent periods were affected by the Great Recession and are unrepresentative of the long term trend of the US economy.

[24] For calibration of this parameter government spending is combined with net exports of goods and services.

[25] Havránek (2015) conducted a meta-analysis on estimates of the EIS and recommended that its value should be calibrated at no larger than 0.8 to be consistent with "the bulk of empirical evidence," which implies that $\sigma_c$ should be calibrated at no less than 1.25. Crump et al. (2015) estimated the (subjective) EIS to be around 0.8 in the general US population with data from the Survey of Consumer Expectations. Because Crump et al.'s data included measures of households' expectation of future consumption expenditures and inflation, the authors were able to circumvent intricacies in the process of expectation formation, which challenge traditional estimation of the consumption Euler equation, and estimate directly the elasticity of *expected* consumption growth to variation in the ex ante real interest rate across individuals.

by Christiano et al. (2005). The calibration of all sectoral price markups being the same completely eliminates relative price dispersion in the steady state, i.e., $\overline{\varphi}(s) = 1$, for all $s = 1, \ldots, S$. The inverse of the elasticity of substitution between composite consumption goods in different sectors is set to $\nu = 2.5$, implying that intersectoral substitution is fairly inelastic. The variances of the measurement errors are fixed at 5% of the corresponding data series in the measurement equations for output, consumption, investment, and all the inflation rates. The variances of the measurement errors in the measurement equations for labor supply, the real wage, and the interest rate are fixed at 10% of the corresponding data series.

[Table 3 about here.]

Table 3 compares some steady-state variables, including certain "great ratios" as well as the interest rate and the inflation rate, in the model and their counterparts in the data over the period of 1985Q1–2008Q2. The calibrated model is able to replicate the selected features of the data in general, except that the steady-state capital stock–GDP ratio and steady-state inflation are lower in the model.[26,27]

### 4.4 Priors

I employ endogenous priors à la Christiano et al. (2011). This procedure starts with an initial set of independent priors and then updates the priors with information on standard deviations of the data in a "pre-sample," which is taken to be the actual sample used in estimation. The initial priors of the estimated parameters are specified in Tables 4–7 and described in what follows.

The prior of the habit parameter $h$ is centered at 0.7 with a standard deviation of 0.1, which is common in the literature. For the re-parameterized curvature of the capital utilization cost function, $\kappa_z$, I follow Smets and Wouters (2007) and set a prior with a mean of 0.5 and a standard deviation of 0.15. For the re-parameterized curvature of the investment adjustment cost function, $\kappa_i$, I center the prior at 0.8 with a smaller standard deviation of 0.1. With $\kappa_i = 0.8$, the implied original curvature of the investment cost adjustment function is $S''_i = \kappa_i/(1 - \kappa_i) = 4$, which is a value widely used in the literature for the prior mean of the parameter $S''_i$. The prior for Calvo wage stickiness $\theta_w$ is centered at 0.75, which implies an average wage contract length of one year, and a standard deviation of 0.1. The prior for the degree of wage indexation has a mean of 0.5 and a standard deviation of 0.15. These priors are also common in the literature.

[26] Gomme and Lkhagvasuren (2012) argued that measuring capital stock can be challenging due to issues such as what to include in the measure and large data revisions. The authors suggested that calibrating the model to target the capital–output ratio "seems unwise."

[27] Given that the model's steady-state growth rate of output is matched with the subsample average growth rate of real GDP per capita and that $\sigma_c = 1.25$, the model has difficulty to simultaneously replicate the subsample average interest rate and the subsample inflation rate unless the households' discount factor is set to a value extremely close to one, which is less favorable.

Turn to the sector-specific structural parameters. The parameters of sectoral Calvo price stickiness $\{\theta_p(s)\}_{s=1}^S$ are given the same, relatively disperse prior with a mean of 0.5 and a standard deviation of 0.125. A prior with a mean of 0.5 and a standard deviation of 0.15 is used for all the parameters of sectoral price indexation $\{\iota_p(s)\}_{s=1}^S$.

Turn to the monetary policy parameters. The policy smoothing parameter $\rho_r$ has a prior with a mean of 0.75 and a standard deviation of 0.1. The central bank's strength of response to the output gap, $\rho_x$, has a normal prior with a mean of 0.125 and a standard deviation of 0.05. These specifications are taken from Smets and Wouters (2007). For the strength of response to aggregate inflation under the single-inflation-target scheme (model $\mathscr{M}_1$) and the strength of overall response to target inflation under the multi-inflation-target scheme (model $\mathscr{M}_2$), the normal prior has a mean of 1.75, which is larger than the more commonly used value of 1.5, and a relatively tight standard deviation of 0.2. This prior is truncated at 1.0001.

For all the parameters pertaining to the sectoral weights in the central bank's target inflation index, $\rho_\pi^{**}(s)$, $s = 1, \ldots, S$, which are only applicable under the multi-inflation-target scheme (model $\mathscr{M}_2$), I use a normal prior with a zero mean and a large standard deviation of 0.5. Due to the restriction (10), $\rho_\pi^{**}(s)$, $s = 1, \ldots, S$, cannot all be freely estimated, so in practice one of them is not directly estimated but inferred from the other direct estimates via the restriction (10). I choose to not directly estimate $\rho_\pi^{**}(7)$.[28] The left tail of the loose prior on $\rho_\pi^{**}(s)$ allows zero weight on inflation in sector $s$.

Finally, turn to the parameters for shocks and innovations. I specify a prior with a mean of 0.5 and a standard deviation of 0.2 for all AR(1) coefficients of shocks, which is standard in the literature. I specify priors for 100 times the standard deviations of the innovations. With a few exceptions, a prior with a mean of 0.2 and a standard deviation of 0.33 is used. Recall that I have scaled some of the shocks and the corresponding innovations. The priors are specified for the scaled ones whenever applicable.

Exceptions are made on the basis that an innovation may be badly scaled, which mostly affects the sectoral price markup innovations. These innovations are scaled by factors that tend to decrease the sizes of the scaled ones and vary negatively with the estimated degrees of price stickiness in the corresponding sectors. The data show that in the estimation sample quarterly inflation in sector 3 (gasoline and other energy goods) has a standard deviation much larger than those in the other sectors (see Table 1). In addition, micro evidence suggests that, among the twelve sectors, sector 3 might be the sector with the most flexible prices, as price change in the sector is the most frequent (see Table 8 below). These two observations together indicate that the scaled sector-specific component of the price markup shock in sector 3 might have a size much larger than those in the other sectors. Hence I choose a prior with a large mean of 4.0 and a large standard deviation of 6.67 for $100\tilde{\sigma}_p(3)$.

[28]Sector 7 is chosen because over the estimation sample it has a relatively small consumption expenditure share and its sectoral price level is closest to the overall price level on average. The estimation results are robust to the choice of $\rho_\pi^{**}(s)$ to be excluded from the set of directly estimated parameters.

Micro evidence also suggests that, among the twelve sectors, sector 6 (health care) might be the one with the stickiest prices as price change in the sector is the most infrequent (see Table 8 below). Thus the scaling factor applied in sector 6 might be the smallest, resulting in the scaled price markup innovation in sector 6 having a too small size. As a result, I use a prior with a lowered mean of 0.1 and a standard deviation of 0.33 for $100\tilde{\sigma}_p(6)$.

## 4.5 Estimation results

In this subsection I present and discuss at length the estimation results, including the posteriors, variance decomposition, and the impulse response functions of the relative prices to a monetary policy shock. Identification tests à la Iskrev (2010) reveal that the estimated parameters in both model $\mathscr{M}_1$ and model $\mathscr{M}_2$ are locally identified at the respective posterior modes.

### *4.5.1 Posteriors and model comparison*

Tables 4–7 report the posterior modes and the standard deviations of the estimated parameters in the two models $\mathscr{M}_1$ and $\mathscr{M}_2$, which differ only in the equipped monetary policy scheme. In general, the posterior standard deviations are smaller than the respective prior standard deviations, indicating that the data used in estimation have been informative. The exceptions are many of the sector-specific monetary policy parameters in $\mathscr{M}_2$, for which the data are less informative.

[Table 4 about here.]

*Model comparison.* I start with a comparison of the two estimated models. Most of the posteriors of the non-monetary-policy parameters are close in the two estimated models. For comparable monetary policy parameters (Panel B of Table 4), $\mathscr{M}_2$ has a much lower smoothing parameter ($\rho_r$), a higher strength of response to aggregate or overall inflation ($\rho_\pi$ versus $\rho^*_\pi$), and a much lower strength of response to the output gap ($\rho_x$) than $\mathscr{M}_1$ does. The (Laplace approximated) marginal log-likelihood of $\mathscr{M}_2$ is 16.3 log points more than that of $\mathscr{M}_1$, which gives a Bayes factor of exp(16.3) and provides very strong evidence against $\mathscr{M}_1$ per interpretation by Kass and Raftery (1995).[29] Given my interpretation of the monetary policy scheme in $\mathscr{M}_2$, the rejection of $\mathscr{M}_1$ by the data suggests that over the sample period the Fed's responses to sectoral inflation rates seemed different from what they would have been if the Fed had been targeting the aggregate inflation rate and weighting the sectors with their natural weights, i.e., consumption expenditure shares. In other words, the Fed seemed to have targeted a customized index of inflation rather than the aggregate inflation rate. Since the data favor $\mathscr{M}_2$, the remainder of the discussion will focus on $\mathscr{M}_2$.

[29] Kass and Raftery (1995) interpreted twice the natural logarithm of the Bayes factor being larger than 10 or the Bayes factor being larger than 150 as very strong evidence against the null model.

*Posteriors of the sector-specific monetary policy parameters.* Recall that $\rho^{**}_{\pi}(s)$ represents the relative difference of the weight of sector-$s$ inflation in the central bank's index of overall inflation from the natural one, and that $\rho^{*}_{\pi}(s)$ is the actual weight ($s = 1, \ldots, S$). The posterior modes and standard deviations of $\rho^{**}_{\pi}(s)$, $s = 1, \ldots, S$, are listed in the sixth column and the seventh column of Table 5, respectively. The inferred modes and standard deviations of $\rho^{*}_{\pi}(s)$, $s = 1, \ldots, S$, are listed in the seventh column and the eighth column of Table 5, respectively.

[Table 5 about here.]

Taking the standard deviations into consideration, I find that most of the posterior distributions of $\rho^{**}_{\pi}(s)$ have the majority of their densities not far away from zero, implying that the sectoral weights in the Fed's customized index of overall inflation seemed no different from the corresponding natural weights for most of the sectors over the sample period. Several exceptions emerge: sector 3 (gasoline and other energy goods), sector 6 (health care), sector 5 (housing and utilities), and sector 10 (financial services and insurance). For sector 3 and sector 6, the majority of the posterior densities of $\rho^{**}_{\pi}(s)$ are located far away from zero, and the inferred actual weights ($\rho^{*}_{\pi}(s)$) are virtually zero, implying that the Fed did not seem to respond to inflation in the two sectors at all during the sample period. The posterior mode of $\rho^{**}_{\pi}(10)$ is moderately negative, suggesting that the Fed responded possibly weakly to inflation in sector 10. On the other hand, the estimated mode of $\rho^{**}_{\pi}(5)$ is positive and large, implying that over the sample period the Fed responded to inflation in sector 5 more aggressively than it would have done if it had targeted aggregate inflation.

The exclusion of inflation in sector 3 from the Fed's estimated index of overall inflation appears no surprise, given the Fed's past focus on core PCE inflation, which excludes food and energy inflation[30]. However, had the Fed targeted core PCE inflation and not responded to inflation in food prices over the sample period, the estimated weight on sector-1 (food and beverages purchased for off-premises consumption) inflation, $\rho^{*}_{\pi}(1)$, should have been much lower. The difference suggests that the Fed treated food prices and energy prices very differently during the sample period.

The estimated zero weight on sector-6 inflation and the estimated extra weight on sector-5 inflation in the Fed's index of overall inflation are somewhat surprising. It remains unclear why the Fed seemed to not respond to changes (most likely increases) in the price of health care at all over the sample period. Perhaps it was because among the twelve sectors, sector 6 was the most inflationary sector over the sample period (see Table 1), and thus the Fed thought changes in the price of health care were not indicative of the trend inflation. However, over the sample period inflation rates in sector 5 had the third largest mean and the second smallest standard deviation among the twelve sectoral inflation rates

[30] The BEA defines "food" consisting of food and beverages purchased for off-premises consumption (sector 1 in this paper) and defines "energy" consisting of gasoline and other energy goods (sector 3 in this paper) and of electricity and gas services (a subcategory in sector 5 in this paper).

(see Table 1). If the Fed was simply avoiding the most inflationary sectors, it should perhaps lower the weight on sector-5 inflation as well, instead of putting extra weight on sector-5 inflation.

Based on the estimated weights at the posterior mode, the Fed's overall behavior in response to inflation during the sample period seemed to be targeting an index of overall inflation consisted of inflation in all sectors except sector 3 (gasoline and other energy goods) and sector 6 (health care), weighted by the sectoral consumption expenditure shares except for sector 5 (housing and utilities), of which the weight was larger, and sector 10 (financial services and insurance), of which the weight was possibly smaller.

*Posteriors of the non-sector-specific structural parameters.* The posterior mode of the habit parameter turns out somewhat larger than the values commonly obtained in other DSGE models estimating this parameter (e.g., Smets and Wouters 2007, Christiano et al. 2011), but not excessively large compared to the values obtained by Fuhrer (2000). The estimated curvature of the cost function of setting capital utilization is very large. At the posterior mode, $\kappa_z = 0.94$ implies $\sigma^z = 15.2$, which is much larger than estimates in the literature (e.g., Smets and Wouters 2007, Christiano et al. 2011). The estimated curvature of the investment adjustment cost function is in line with estimates in the literature. At the posterior mode, $\kappa_i = 0.88$ implies a large cost in adjusting investment, with the original curvature parameter $S_i'' = 7.51$. The posterior of Calvo wage stickiness ($\theta_w$) suggests a more flexible wage than it is assumed in the prior, with the average wage contract length equal to 2.4 quarters at the posterior mode. The degree of wage indexation is estimated to be low. The findings on the degrees of wage stickiness and wage indexation here differ from those by Smets and Wouters (2007), who found both a stickier wage and a higher degree of wage indexation. Among the non-sector-specific shocks, the wage markup shock, the common component of the price markup shocks, and the risk premium shock appear to be short-lived,[31] while the technology and the MEI shock seem to be more persistent.

*Posteriors of the sector-specific characteristics.*

[Table 6 about here.]

[Table 7 about here.]

Turn to the parameters of the sector-specific characteristics, which are collected in Tables 6–7. The posterior modes of sectoral Calvo price stickiness ($\theta_p(s)$, $s = 1, \dots, S$) are larger than 0.72 for all sectors except sector 3 (gasoline and other energy goods), and are

[31] A short-lived wage markup shock is not uncommon in the literature. Smets and Wouters (2007) added a first-order moving average (MA(1)) component to the wage markup shock to account for high-frequency variation in the real wage. In this paper's model, however, adding an MA(1) component is less favorable because the MA(1) coefficient and the existing AR(1) coefficient of the wage markup shock cannot be individually identified in estimation. Christiano et al. (2011) pointed out that, without an extensive margin, any change in labor supply (on the intensive margin) had to be from a change in the real wage, and thus such a model needed high-frequency variation in real wage to match the data for labor supply.

mostly above 0.87, suggesting substantial price stickiness in the majority of sectors. Looking across sectors, I find some dispersion in the posterior modes, indicating heterogenous price stickiness across sectors. I note that the estimated Calvo probabilities should be interpreted with caution here, since they reflect the frequencies of producers *re-optimizing* their prices rather than simply *changing* the prices in a model with price indexation. The price of a good can change in every period since producers always index their prices whenever they are not given the chance to re-optimize their prices. Nonetheless, the estimated sectoral Calvo probabilities do capture some of the cross-sectional difference in the average frequency of price change evidenced by micro data.

[Table 8 about here.]

Table 8 compares across sectors the estimated degree of sectoral price stickiness at the posterior mode with the average monthly "infrequency" of price change reported in Carvalho and Lee (2011, Table 16). Carvalho and Lee matched Bils and Klenow's (2004) micro data on the frequency of price change to disaggregate PCE categories, and their 15-sector specification consisted of sectors matching the ones used in this paper. The sectors are ranked in terms of their price stickiness. The estimated model successfully identifies the sector with the stickiest prices—sector 6 (health care), the sectors with the most price flexibility, such as sector 3 (gasoline and other energy goods) and sector 1 (food and beverages purchased for off-premises consumption), and some sectors in the middle of the spectrum of price stickiness, such as sector 4 (other nondurable goods). On the other hand, multiple sectors are ranked very differently. For instance, the estimated model ranks sector 10 (financial services and insurance) relatively low whereas the micro data rank it the second highest. An opposite instance is that sector 2 (clothing and footwear) is ranked the third by the estimated model whereas it is given a below-average rank by the micro data. Basing on the results of comparison, I find that the estimated model is, in general, capable of qualitatively accounting for the difference in the average frequency of price change of individual goods across consumption sectors evidenced by the micro data, without access to data on individual prices.[32]

I find low to moderate degrees of sectoral price indexation, in line with the findings by Smets and Wouters (2007) and Christiano et al. (2011), and there is also dispersion in the degree of price indexation across sectors ($\iota_p(s)$ ranging from 0.11 to 0.49). For the sector-specific components of the price markup shocks, persistence ($\rho_p(s)$) varies greatly across sectors. For instance, sector 12 (final consumption expenditures of NPISHs) has the most persistent sector-specific shock component ($\rho_p(12) = 0.97$) while sector 7 (transportation services) has the least persistent one ($\rho_p(7) = 0.27$). Yet, all of the sector-specific shock

[32] Alternatively, I run a simple linear regression of the statistics in the fifth column of Table 8 on the estimated Calvo probabilities in the third column of the table. The slope estimate is positive and statistically significantly non-zero at the 10% level (with bootstrapped standard error). The regression has $R^2 = 0.76$.

components are relatively more persistent than the common shock component (see Panel C of Table 4).

The true sizes of the price markup innovations are unclear from Table 7, since Table 7 only shows the estimates of the scaled ones. I recover the estimated standard deviations of the unscaled innovations underlying the sector-specific components of the price markup shocks as well as the one underlying the common component at the posterior mode in the third column and the second column of Table 9, respectively. Then I decompose the standard deviations of the unscaled price markup shocks ($\mathrm{sd}(\hat{\epsilon}_t^p(s))$) into a common component ($\mathrm{sd}(\hat{\zeta}_t^p)$) plus the sector-specific components ($\mathrm{sd}(\hat{\zeta}_t^p(s))$, $s = 1, \ldots, S$) in the last three columns of Table 9. I have three observations from Table 7. First, the size of the sector-specific innovation differs vastly across sectors, with the largest ($100\,\mathrm{sd}(\hat{\eta}_t^p(2)) = 120.1$) more than eighty-four times as large as the smallest ($100\,\mathrm{sd}(\hat{\eta}_t^p(1)) = 1.42$). Second, at the shock level, the sector-specific component ($\hat{\zeta}_t^p(s)$) dominates the common component ($\hat{\zeta}_t^p$) in size. Third, the sector-specific shock components in sector 1 (food and beverages purchased for off-premises consumption) and sector 5 (housing and utilities) have the smallest standard deviations among all.

[Table 9 about here.]

#### 4.5.2 *Model moments and variance decomposition*

[Table 10 about here.]

Table 10 compares the standard deviations of the observed time series that enter the measurement equations and those of the corresponding observable variables in the model. The model generally matches the data well owing to the endogenous priors. For some variables (e.g., growth of real investment per capita and growth of labor supply per capita), the model standard deviations deviate moderately but not excessively from the corresponding data standard deviations.

[Table 11 about here.]

Table 11 presents the unconditional variance decomposition of selected endogenous variables at the posterior mode. Observe first that the MEI shock dominates the other shocks in variance decomposition of most real variables including output, consumption, investment, and labor supply as well as in variance decomposition of the nominal interest rate, which is partly in line with Justiniano et al.'s (2011) finding that the MEI shock was the primary driver of output, investment, labor supply, and the nominal interest rate at business cycle frequencies.[33] The technology shock is the most important driver of the real

[33] Justiniano et al.'s (2011) found that the MEI shock only explained a small fraction of consumption variation in business cycle frequencies. While Justiniano et al.'s (2011) model had an intertemporal preference shock, the models considered here ($\mathscr{M}_1$ and $\mathscr{M}_2$) do not.

wage and the second most important driver of output, consumption, and investment in the long run.

The sector-specific price markup shocks, which include a common component and sector-specific components, mostly do not contribute or contribute marginally to long-run variations in real variables. A notable exception is the sector-specific component in sector 6 (health care), which explains almost 20% of long-run variation in the real wage and turns out to be a more important driver of the real wage in the long run than the wage markup shock is. The monetary policy shock contributes marginally to long-run variations in real variables, while it is the second most important driver of the nominal interest rate in the long run. The risk premium shock or the government spending shock, however, contributes only marginally to variations in all variables in the long run.

The price markup shocks together account for over 77% of long-run variation in aggregate inflation. This result differs from the finding by Smets and Wouters (2007) that the wage markup shock rather than the price markup shock accounted for the most of long-run variation in aggregate inflation. The "aggregate" shocks, i.e., shocks other than the sector-specific components of the price markup shocks, together only explain about 27% of long-run variation in aggregate inflation, while the sector-specific shock components explain about 73% of long-run variation in aggregate inflation. This result stands in contrast to Boivin et al.'s (2009) finding that volatility of aggregate PCE inflation is mostly due to aggregate fluctuations. On the other hand, Bouakez et al. (2014) found in an estimated DSGE model with heterogenous sectors that sector-specific productivity shocks explained 39–50% of long-run variation in aggregate inflation. Looking at the sector-specific components, I find that the sector-specific component in sector 3 (gasoline and other energy goods) explains a dominant proportion of 51.1% of long-run variation in aggregate inflation. Bouakez et al. (2014) also found that a significant fraction (14–19%) of long-run variation in aggregate inflation was explained by the oil productivity shock. Additionally, the sector-specific shock components in sector 6 (health care) and sector 10 (financial services and insurance) have nontrivial contributions to variation in aggregate inflation in the long run.

Turn to decomposition of the sectoral inflation rates. Long-run variation in the sectoral inflation rates is mostly explained by the sector-specific components of the price markup shocks in the individual sectors, but the proportions being explained vary by sector. This result is broadly in line with the findings by Boivin et al. (2009) and De Graeve and Walentin (2015). De Graeve and Walentin refined Boivin et al.'s FAVAR to control for measurement error, sales, and item substitution and found that in one out of four sectors aggregate shocks accounted for more variation in sectoral inflation than sector-specific shocks did, while the proportion is one out of twelve in this study.

The two sectors in which more than 45% of long-run variation in sectoral inflation rates is explained by aggregate shocks are sector 1 (food and beverages purchased for off-premises consumption) and sector 5 (housing and utilities). There is a third sector, sector 9 (food services and accommodations), in which the proportion is over 43% and is the third largest among those of all sectors. A common trait of the three sectors is the size of the sector-specific component of the price markup shock being relatively small (see Table 9). A cross-sectional regression predicts a statistically significant decrease in the proportion of long-run variation in sectoral inflation explained by aggregate shocks, denoted $\mathrm{VD}_\infty(\hat{\pi}(s), \mathrm{AGG})$, when the logarithm of the estimated standard deviation of the sector-specific shock component in the same sector, $\ln \mathrm{sd}(\hat{\zeta}_t^p(s))$, increases.[34]

#### 4.5.3 *Impulse response functions of the relative prices to a monetary policy shock*

Now I examine how the sectoral relative prices, $\hat{\varphi}_t(s)$, $s = 1, \dots, S$, and growth of the sectoral relative prices, $\Delta\hat{\varphi}_t(s)$, $s = 1, \dots, S$, respond to a monetary policy shock. Figure 1 shows the impulse response functions of these endogenous variables to a contractionary, one-standard-deviation monetary policy shock at the posterior mode. Recall the discussion in Section 3 on the relationship between the sectoral relative price and sectoral output and the relationship between growth of the sectoral relative price and sectoral inflation in the model.

[Figure 1 about here.]

The monetary policy shock generates cross-sectional dispersion in sectoral relative prices (Figure 1a and Figure 1b). The responses of the sectoral relative prices are generally hump-shaped. The time at which the maximum (in absolute value) response occurs varies by sector but is mostly 3–7 quarters after the shock hits the economy. Note that this time range indicates the approximate time after a monetary policy shock at which the shock generates most dispersion in relative prices. The distribution of the signed maximum responses in absolute value (i.e., maxima in absolute value but with the same sign as the actual values) across sectors seems asymmetric: Negative signed maximum responses (e.g., the ones in sectors 3 and 1) tend to be larger in absolute value than positive signed maximum responses (e.g., the ones in sectors 6 and 11).

Looking at individual sectors, I observe that the relative-price response in sector 3 (gasoline and other energy goods) has the most negative signed maximum and peaks in absolute value earliest, while the relative-price response in sector 6 (health care) has the most positive signed maximum. This observation implies that, in the face of a contractionary monetary policy shock, prices in sector 3 fall the most, resulting in sector-3 output falling the least, while the prices in sector 6 fall the least, resulting in sector-6 output falling the most.

[34] In the cross-sectional regression of $\mathrm{VD}_\infty(\hat{\pi}(s), \mathrm{AGG})$ on $\ln \mathrm{sd}(\hat{\zeta}_t^p(s))$, the sector size $\omega_s$, and a constant, the estimated coefficient of $\ln \mathrm{sd}(\hat{\zeta}_t^p(s))$ is $-0.18$ with a bootstrapped standard error of 0.03. The estimated coefficient of $\omega_s$ is insignificant at any conventional level. The regression has 12 observations and $R^2 = 0.89$.

The monetary policy shock also generates cross-sectional dispersion in growth of the sectoral relative prices (Figure 1c and Figure 1d). The maximum responses of growth of the relative prices generally occurs immediately after the shock. The dispersing effect of the monetary policy shock on growth of the relative prices dies out more quickly than its dispersing effect on the relative prices does. Looking at individual sectors, I observe that sector 3 (gasoline and other energy goods) and sector 6 (health care) have the most negative and the most positive responses of growth of the relative prices, respectively, implying that sector 3 is the most disinflationary sector and sector 6 is the least disinflationary sector in the face of a contractionary monetary policy.

How responsive a sectoral relative price and its growth are to a monetary policy shock may depend on price flexibility and the degree of price indexation in the sector. A number of studies found empirically a positive, significant cross-sectional relationship between sectoral price flexibility and the speed or the magnitude of the responses of sectoral prices to an aggregate shock (see, e.g., Maćkowiak et al. 2009, Kaufmann and Lein 2013, Bouakez et al. 2014). Denote the response of the relative price ($\hat{\varphi}_t(s)$) and the response of growth of the relative price ($\Delta\hat{\varphi}_t(s)$) in sector $s$ ($s = 1, \ldots, S$) $t$ quarters after the monetary policy shock hits the economy by $\text{IRF}_t(\hat{\varphi}(s), \eta^r)$ and $\text{IRF}_t(\Delta\hat{\varphi}(s), \eta^r)$, respectively. Responsiveness may be indicated by the signed maximum response (marked by crosses in Figure 1), denoted by $\text{IRF}^{\text{m}}(x, \eta^r)$, or the cumulative response $\text{IRF}^{\text{c}}(x, \eta^r) = \sum_{t=1}^{40} \text{IRF}_t(x, \eta^r)$, where $x$ is $\hat{\varphi}(s)$ or $\Delta\hat{\varphi}(s)$. Table 12 presents the results from cross-sectional regressions of these measures of responsiveness on the estimated degrees of sectoral price flexibility and price indexation. The size of the sector ($\omega_s$) is also included as a control variable. To better exploit cross-sectional variation in the variables of interest, I apply a monotonic transformation function

$$f(x) = \ln\left(\frac{x}{1-x}\right), \quad x \in (0, 1),$$

to both the estimated degrees of sectoral price stickiness and the estimated degrees of sectoral price indexation, and enter the transformed variables in the cross-sectional regressions. The regression results show that, in line with previous studies, relative prices or their growth in sectors with more price flexibility (a lower $\theta_p$(s)) tend to be more responsive to a monetary policy shock, holding the degree of price indexation and the sector size constant. The regression results also show that dynamic price indexation ($\iota_p(s)$) may further increase responsiveness of sectoral relative prices to a monetary policy shock.

[Table 12 about here.]

## 5 Optimal Monetary Policy in the Estimated Model

In this section I try to address the following questions: How does the monetary policy in the estimated model, under which the central bank targets a customized index of sectoral inflation rates, compare in terms of welfare to an alternative policy scheme under which the central bank targets a different inflation index? How should the central bank optimally compose an index of overall inflation from sectoral inflation rates to maximize household welfare? I approach these questions by first proposing a numerical procedure to evaluate welfare of the representative household in the estimated model. Then I compare in terms of welfare the baseline monetary policy with alternative policy schemes in which the target index of inflation is randomly composed, and finally I consider the optimal composition of the index of overall inflation to be targeted by the central bank. All results in this section are based on the estimated model $\mathcal{M}_2$ at the posterior mode.

## 5.1 The procedure for welfare evaluation

### *5.1.1 Definitions*

For welfare evaluation I focus on the expected utility of the representative household in period 0:

$$\mathcal{U}(\mathcal{R}) = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U_t(\mathcal{R}), \tag{15}$$

where $U_t(\mathcal{R})$ is the period-$t$ utility of the representative household given the set of monetary policy parameters $\mathcal{R}$. Welfare of the representative household in the steady state, which is independent of the monetary policy in effect, can be derived as a function of steady-state consumption $\bar{c}$:

$$\overline{\mathcal{U}} = \overline{\mathcal{U}}(\bar{c}) = A_0 \bar{c}^{1-\sigma_c},$$

where $A_0$ is a constant independent of $\bar{c}$.

In the model economy with shocks and frictions, the steady-state welfare level $\overline{\mathcal{U}}$ in general cannot be achieved, i.e., $\mathcal{U}(\mathcal{R}) < \overline{\mathcal{U}}$ in general. To facilitate welfare comparison and interpretation, consider the following equation:

$$\mathcal{U}(\mathcal{R}) = \overline{\mathcal{U}}\big((1 + \delta_c(\mathcal{R}))\bar{c}\big), \tag{16}$$

where $\delta_c = \delta_c(\mathcal{R})$, generally negative and usually quoted in percentage, can be interpreted as the amount by which steady-state consumption needs to be exogenously permanently increased in order to achieved the welfare level $\mathcal{U}(\mathcal{R})$ under monetary policy $\mathcal{R}$. I refer to the absolute value of $\delta_c$ as the welfare gap. Since $\overline{\mathcal{U}}(\bar{c})$ is an increasing function of $\bar{c}$, $\delta_c(\mathcal{R}_1) < \delta_c(\mathcal{R}_2)$ is equivalent to $\mathcal{U}(\mathcal{R}_1) < \mathcal{U}(\mathcal{R}_2)$, which implies that the representative household is worse off under policy $\mathcal{R}_1$ than he or she is under policy $\mathcal{R}_2$.

### *5.1.2 Numerical approximation of $\mathcal{U}(\mathcal{R})$ via simulation*

I choose to approximate $\mathcal{U}(\mathcal{R})$ defined in (15) numerically by repeatedly simulating the log-linearized model and computing the approximation from the simulated data. Several difficulties with this approach arise. First, the summation in (15) is an infinite series while in practice only a finite number $T$ of terms can be included in summation. I set $T = 7{,}500$ so that the truncation error is sufficiently small.[35] Second, $\mathcal{U}(\mathcal{R})$ depends on the initial state of the economy, which is unspecified. I make the assumption that the initial state of the economy is a random draw from the unconditional distribution of the state of the economy in the log-linearized model. In practice, I simulate the model starting in the steady state for a total of $T_d + T$ periods, where $T_d = 1{,}000$, and discard the data in the first $T_d$ periods, in the hope that the simulated state of the economy after $T_d$ periods closely resembles a random draw from the unconditional distribution of the state of the economy.

Third, the expectation $\mathbb{E}_0$ in (15) is taken over all possible current and future states of the economy, while in practice only a finite number of states can be produced by simulation. I refer to a complete path of length $T$ of all endogenous variables in the model as a replication. I approximate the expectation by averaging over $N = 2{,}500$ replications. In general, the more replications one has, the better approximation to the expectation $\mathbb{E}_0$ can be.[36] Denote the utility of the representative household computed from the simulated data in period $t$ ($t = 0, \ldots, T-1$) of replication $n$ ($n = 1, \ldots, N$) by $U_{n,t}(\mathcal{R})$. Then the representative household's approximate lifetime utility in replication $n$ ($n = 1, \ldots, N$) is $U_n^{\approx}(\mathcal{R}) = \sum_{t=0}^{T-1} \beta^t U_{n,t}(\mathcal{R})$, and the approximated expected utility by simulation is given by

$$\mathcal{U}^{\approx}(\mathcal{R}) = \frac{1}{N} \sum_{n=1}^{N} U_n^{\approx}(\mathcal{R}) = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=0}^{T-1} \beta^t U_{n,t}(\mathcal{R}).$$

The $\delta_c(\mathcal{R})$ implied from (16) with the approximated $\mathcal{U}^{\approx}(\mathcal{R})$ is denoted by $\delta_c^{\approx}(\mathcal{R})$. In practice, I start by generating a total of $N$ replications of complete paths of length $T_d + T$ of the exogenous shocks, from which the paths of all endogenous variables and the approximated expected utility can be computed. The replications of the exogenous shocks form the base of the simulated sample data and are fixed throughout subsequent analysis.

### 5.2 Preliminary welfare evaluation: How good is the baseline policy?

Now I attempt to address the first question posed earlier: How good is the baseline monetary policy in the estimated model in terms of welfare of the representative household, and how does it compare to alternative policy schemes? I restrict alternative policy schemes for welfare comparison, for now, to be within the class of policy schemes in which a policy scheme may differ from the baseline scheme only in the composition of the target index of overall inflation. In other words, the set $\mathcal{R}$ of monetary policy parameters to be optimized includes $\rho_\pi^*(s)$, $s = 1, \ldots, S$, while the policy smoothing parameter $\rho_r$, the strength of

[35]The relative truncation error for summation in the steady state is about $1.1 \times 10^{-8}$ when $T = 7{,}500$.

[36]Unfortunately, the precision of the average as measured by its standard error decreases at the speed of $\mathcal{O}(1/\sqrt{N})$, while the number of arithmetic operations required for computation increases at the speed of $\mathcal{O}(N)$. This observation suggests that the approximation approach considered here is at computational disadvantage.

response to overall inflation $\rho^*_\pi$, and the strength of response to the output gap $\rho_x$ are fixed at their respective baseline values. Denote the parameter set of the baseline monetary policy by $\mathscr{R}_0$.

I obtain alternative policy schemes by randomly setting their parameters. I conduct two experiments differing in how the parameters are randomly set. In the first experiment ("random draw"), weights of sectoral inflation rates in the target inflation index are first drawn from the uniform distribution on $(0, 1)$ and then normalized to sum to one. The second experiment ("random perturbation") starts with the baseline parameter values. Weights of sectoral inflation rates are first added with random draws from the uniform distribution on $(-0.5, 0.5)$ and then normalized to sum to one. For each experiment, I run 100 trials.

[Table 13 about here.]

Table 13 presents welfare evaluation of the baseline monetary policy and the results from the experiments. The baseline policy $\mathscr{R}_0$ has $\delta^{\approx}_c(\mathscr{R}_0) = -0.896\%$, implying a small welfare gap between the estimated model with all the shocks and frictions and the steady state. I have several observations on the results of the experiments. First, the baseline monetary policy seems to perform fairly well in terms of welfare of the representative household. It outperforms all the alternative schemes randomly generated in experiment 1 and 55 out of 100 alternative schemes randomly generated in experiment 2. Second, welfare difference across randomly generated monetary policy schemes is small, especially in experiment 2. The cross-sectional standard deviations of $\delta^{\approx}_c(\mathscr{R})$ are less than 20% of the baseline welfare gap. Third, the baseline policy outperforms the monetary policy scheme under which the central bank targets aggregate inflation, though the difference in terms of welfare (an increase in the welfare gap by 9.7 basis points) is small.

### 5.3 Optimal composition of the target index of inflation

Next, I turn to the second question posed earlier: How should the central bank optimally compose the target index of inflation from sectoral inflation rates to maximize household welfare?

*The central bank's optimization problem.* I assume that the central bank's objective is to maximize welfare of the representative household, possibly subject to certain constraints, by choosing a set of parameters $\mathscr{R}$, which comprises the weights of sectoral inflation rates. Formally, the central bank's optimization problem is

$$\max_{\mathscr{R}} \mathcal{U}(\mathscr{R}),$$

subject to constraints on parameters in $\mathscr{R}$, where $\mathscr{R} = \{\rho^*_\pi(s;\mathscr{R})\}_{s=1}^S$.

I consider two cases in which the constraints differ. In cases 1 the weights are constrained between zero and one. In cases 2 the weights are not constrained by nonnegativity, which means that the central bank is allowed to respond to inflation in a sector by reducing the interest rate as opposed to the normal behavior of increasing the interest rate for disinflation. The structural restriction (10) applies in all cases. Denote the set of optimal weights in case $d$ ($d = 1, 2$) by $\mathscr{R}_d^*$.

*Results of optimization.*

[Table 14 about here.]

Table 14 presents the results of numerical optimization in the two cases, conditional on the simulated data. Observe, first of all, that welfare improvement from the baseline policy scheme to an optimal policy scheme is very small—less than 16% of the baseline welfare gap, suggesting that the index of overall inflation in the baseline scheme, which the Fed might have been implicitly targeting in the sample period, or the current inflation target of headline PCE inflation adopted by the Fed is almost indistinguishable in terms of welfare from the optimal target index of inflation.

Nonetheless, the composition of the optimal target indices of inflation appears interesting. A prominent pattern is that the inflation rates in sector 1 (food and beverages purchased for off-premises consumption) and sector 5 (housing and utilities) are consistently assigned large weights in the two cases, and the assigned weights are at least 95% more than the corresponding natural ones. On the other hand, the inflation rates in sectors other than sector 1 or sector 5 are given virtually zero weights or weights lower than the corresponding natural ones in case 1, and four sectors are given negative weights in case 2. Based on these observations, the central bank's optimal behaviors seem rather unconventional. When it is constrained by nonnegativity of sectoral weights, the central bank responds very aggressively to inflation in a handful of sectors and remains unresponsive to inflation in most of the remaining sectors. When it is not constrained by nonnegativity of sectoral weights, the central bank may take inflationary rather than disinflationary actions in response to inflation in some sectors.

The optimal sectoral weights also contrast sharply with the baseline ones. Under the baseline monetary policy, the central bank excludes the sectoral inflation rates in sectors 3 and 6 from the target index of overall inflation. This exclusion agrees with zero or negative weights of the corresponding sectoral inflation rates under the optimal policy scheme in either of the two cases. On the other hand, the optimal policy schemes mostly focus on sectoral inflation rates in sectors 1 and 5, but the baseline policy assigns a weight seemingly no different form the natural one to sector-1 inflation and a weight moderately larger than the natural one to sector-5 inflation.

*Discussion.* When the central bank is composing the optimal inflation index to be targeted, why does it assign large, positive weights to the inflation rates in sector 1 and sector 5? And why does the central assign negative weights to sectoral inflation rates in some sectors when it is not constrained by nonnegativity of sectoral weights? Some evidence emerges as I relate the cross-sectional difference in the optimal sectoral weights to the cross-sectional difference in the fraction of unconditional forecast error variance of sectoral inflation explained by aggregate shocks and to the cross-sectional difference in responsiveness of the sectoral relative price to a monetary policy shock, and further to the cross-sectional difference in sectoral characteristics, particularly the size and persistence of the sector-specific component of the price markup shock and price flexibility.

Recall the discussion in Section 4.5.2. A relatively large fraction of unconditional forecast error variance of sectoral inflation in sector 1 as well as in sector 5 is explained by non-sector-specific, aggregate shocks, which is largely due to the relatively small sizes of the sector-specific shock components in the two sectors. Intuitively, the inflation rates in sector 1 and sector 5 contain more information on aggregate shocks, which is helpful for the central bank to access the state of the economy, than inflation rates in the other sectors do. Therefore, the two sectoral inflation rates are assigned large weights in the central bank's optimal target index of inflation. The weight of sector-5 inflation being larger than the weight of sector-1 inflation in case 2 may be attributed to that the sector-specific shock component in sector 5 is relatively less persistent than the sector-specific shock component in sector 1 is.

The explanation in the preceding paragraph is related to Mankiw and Reis's (2003) finding that a sector's price should be assigned a higher weight in the central bank's stability price index if the sector's price was more responsive to the business cycle or if the sector's idiosyncratic shock had a smaller variance, because the former indicated "high signal" and the latter indicated "low noise" in the sector's price and thus such conditions could help the central bank extract information on the business cycle from the sector's price. Per Mankiw and Reis's interpretation, the inflation rates in sector 1 and sector 5 do both have a "low noise," but the inflation rate in sector 5 does not seem to have a "high signal." Mankiw and Reis interpreted high sensitivity of a sector's equilibrium price to the output gap as indication of "high signal," which was more in the sense of large impulse responses to aggregate shocks. However, the relative price of sector 5 may not be particularly responsive to aggregate shocks because prices in sector 5 appear relatively sticky ($\theta_p(5) = 0.873$; also see Figure 1), and thus the sector-5 inflation rate may not be that "signaling" per Mankiw and Reis's interpretation. Yet, sector 5 receives a large weight. I reconcile the disparity by interpreting "high signal" from the perspective of variance decomposition: The inflation rate in a sector has a "high signal" when aggregate shocks account for a large fraction of its forecast error variance. Low persistence of the sector-specific component of the price markup shock may help increase "signal" and reduce "noise" as well. With this interpretation, "high signal" is the exact opposite of "low noise," and both can be assessed by examining the sectoral inflation rate's variance decomposition and persistence of the sector-specific shock component in the sector. On the other hand, inflation rates in sectors of which prices are more responsive to aggregate shocks do no necessarily have "high signals" because prices in those sectors are also more responsive to sector-specific shocks and thus are not necessarily more indicative of economy-wide conditions.

Inflation rates in sectors 2, 6, and 11 are assigned nontrivial negative weights in case 2. Observe that the estimated degrees of price stickiness in the three sectors are ranked highest among all (see the fourth column of Table 8). As a result, the signed maximum responses of the relative prices in these sectors to a contractionary monetary policy shock are all positive, i.e., prices in these sectors fall less than the average price level does in the face of a contractionary monetary policy shock (see Figure 1). Since the central bank prefers high weights for inflation rates in sector 1 and sector 5, from the perspective of inflation targeting, the central bank may be so incentivized as to "borrow" some weights from the sectors with the stickiest prices. Such "borrowing" may be favorable since the sectoral relative prices in the "lending" sectors are hard to move and thus are able to tolerate some distortion (i.e., excessive inflation) caused by the negative weights.

The preceding explanation gives a prescription for how the central bank should optimally adjust the sectoral weights according to sectoral price stickiness that stands in stark contrast to the prescriptions by Aoki (2001), Bodenstein et al. (2008), and Mankiw and Reis (2003). Aoki (2001) found that the central bank should target only the sticky-price sector in terms of welfare when facing two sectors, one with flexible prices and another with sticky prices. Bodenstein et al. (2008) found in a two-sector sticky-wage-and-price model with the flexible-price sector represented by an energy sector that the optimal monetary policy was well approximated by a dual-mandate-type policy with balanced weights on the output gap and core inflation, and that, in the face of a transitory energy price shock, the Taylor rule responding to a forecast of core inflation outperformed the one responding to a forecast of headline inflation in terms of welfare. Mankiw and Reis (2003) found that prices in sectors with more flexible prices should receive less weights in the central bank's stability price index, other things equal.

In Aoki's model, the central bank aimed to eliminate the inefficiency due to price rigidity,[37] and the central bank completely ignored the flexible-price sector because the sector did not contribute to the inefficiency caused by price rigidity. In Bodenstein et al.'s model, energy was an input to production and the wage was sticky, so distortion of the relative price of energy generated additional inefficiency and thus the flexible-price energy sector could no longer be ignored. Yet, welfare loss associated with the additional inefficiency was quantitatively small due to the small contribution of energy in production, and consequently the optimal monetary policy was oriented towards stabilizing core inflation. Both Aoki's and Bodenstein et al.'s model confronted a sticky-price sector with a flexible-price sector, and neither gave prescriptions for what the central bank should do when all prices are sticky and sectors are heterogenous in price stickiness.

[37]The inefficiency due to monopolistic competition was eliminated by employment subsidies.

The intuition Mankiw and Reis provided behind their finding was that large business cycle fluctuations might generate only small price movements in sticky-price sectors because prices in those sectors were hard to move, and thus the central bank wanted to offset such dampening effect of price stickiness by assigning larger sectoral weights to sectors with stickier prices. What Mankiw and Reis referred to as the dampening effect of price stickiness may be explained by (13) (see the discussion in Section 3). The results in this section, however, suggest that the central bank may not want to offset such an effect but to exploit it to further increase the strength of responses to the sectoral inflation rates that the central bank prefers. Note that Mankiw and Reis's finding had an "other-things-equal" clause. While in theoretical analysis it is possible to compare two hypothetical sectors that differ only in one dimension, the central bank in reality is confronted with sectors that are heterogenous in multiple dimensions. Hence applying Mankiw and Reis's finding in the estimated model here may not be straightforward. In addition, I emphasize that the optimal behavior of the central bank in the estimated model is conditional on the assumption that the central bank is optimizing the composition of the target index of inflation while not altering the other aspects of the monetary policy such as the strength of output-gap targeting.[38]

### 5.4 Adjusting the strength of responses

Next, I explore whether the central bank can improve household welfare by adjusting the strength of response to the target index of inflation or the strength of response to the output gap. In what follows the policy smoothing parameter and the composition of the target index of inflation remain fixed at the baseline.

[Table 15 about here.]

Table 15 demonstrates that more aggressive responses to overall inflation or to the output gap can generate substantial improvement in household welfare, and that weak responses may result in massive welfare loss. Note in particular that welfare improvement achieved by more aggressive output-gap targeting can be much larger than welfare improvement achievable by optimizing the composition of the target index of inflation or by very aggressive inflation targeting. Even a moderate increase in $\rho_x$ from the baseline of $\rho_x = 0.140$ to $\rho_x = 0.2$ induces a reduction in the welfare gap by 16.6 basis points, which is about 16% larger than the size of welfare improvement offered by moving to targeting the optimal inflation index. Another interesting finding from Table 15 is that more aggressive responses to overall inflation do not guarantee improved welfare. Increasing $\rho_\pi^*$ from 5 to 10 actually makes the representative household considerably worse off.

[38] As in Erceg et al. (2000), there is a trade-off between output-gap stabilization and inflation stabilization in the model considered here. When optimizing the composition of the target index of inflation, the central bank is still concerned with output-gap stabilization.

## 6 Concluding Remarks

In this paper, I introduce heterogenous sectors into an otherwise standard single-sector New Keynesian DSGE model. I consider sectoral heterogeneities in the sector size, price stickiness, price indexation, and the price markup. These sectoral heterogeneities are crucial in generating the results of this study. Future research may further expand the multisector model to include other types of heterogeneity.

The main goal of this paper is to examine in a structural approach how the central bank should compose a welfare-maximizing target index of inflation from sectoral inflation rates. I find that the central bank should focus on a small subset of sectoral inflation rates when responding to inflation to maximize household welfare and that the sectoral inflation rates with large positive weights in the central bank's optimal index of inflation are the ones containing relatively more information on aggregate shocks. In addition, the central bank may optimally assign negative weights to some sectoral inflation rates and perform unconventional, inflationary monetary policy actions in the corresponding sectors.

I find that the baseline monetary policy in the estimated model performs fairly well in terms of welfare and that the welfare gains achieved by moving to targeting the optimal index of inflation are small. These findings suggest that the current inflation target adopted by the Fed is almost indistinguishable from the optimal one in terms of welfare. On the other hand, more aggressive targeting of the output gap can offer much larger welfare improvement.

Another direction of future research can be to broaden the scope of the central bank's optimization problem to include more targets. A number of studies (e.g., Erceg et al. 2000, Mankiw and Reis 2003) suggested targeting the nominal wage.

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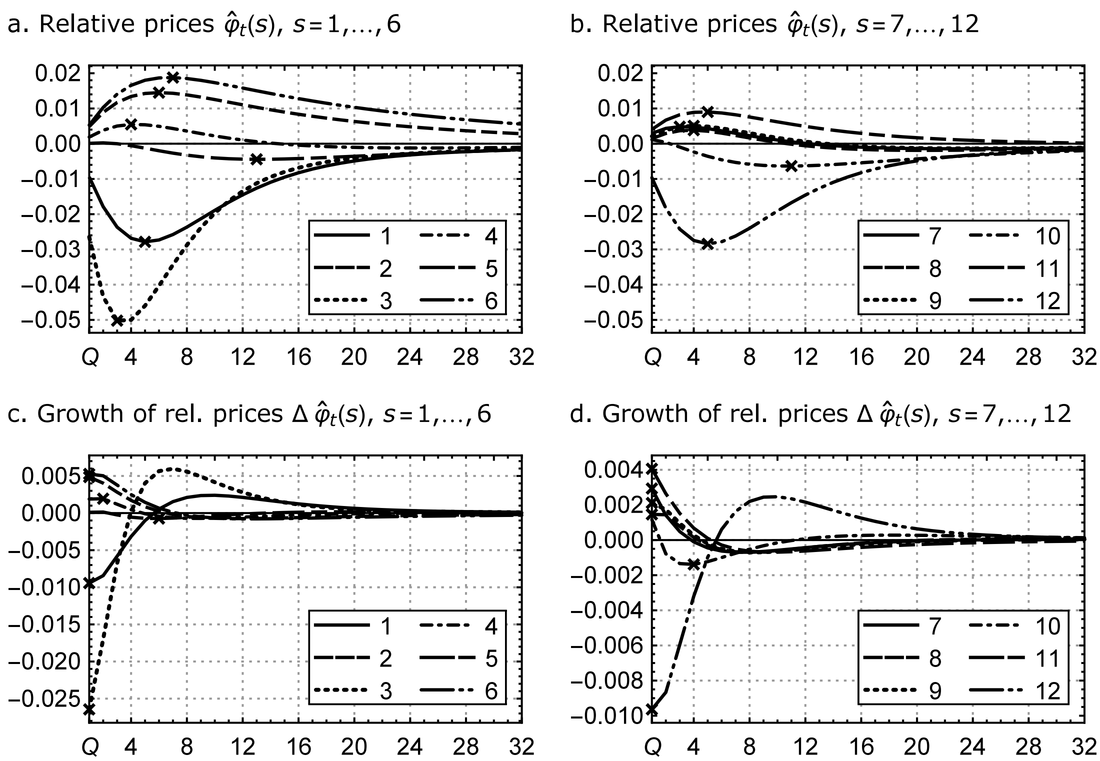


**Figure 1** Impulse response functions of relative prices ($\hat{\pi}_t(s)$, $s = 1, \ldots, S$), and growth of relative prices ($\Delta\hat{\pi}_t(s)$, $s = 1, \ldots, S$) to a contractionary, one-standard-deviation monetary policy shock at the posterior mode

*Note*. In each graph the horizontal axis is the number of quarters after the shock hits the economy and the vertical axis is the response of the endogenous variable, i.e., percentage deviation from the steady state. The signed maximum responses are marked with crosses.

**Table 1** Sectors of the consumption-good market, their average consumption expenditure shares, and their inflation profiles

| $s$ | Sector name[a] | Average consumption expenditure share[b] ($\omega_s^{ob}$) | Sectoral inflation[c] | |
|---|---|---|---|---|
| | | | Mean | SD |
| Nondurable goods | | 0.270[d] | 0.45[e] | 2.44[e] |
| 1 | Food and beverages purchased for off-premises consumption (p.f.o.p.c.) | 0.099 | 0.58 | 0.54 |
| 2 | Clothing and footwear | 0.048 | –0.02 | 0.73 |
| 3 | Gasoline and other energy goods | 0.035 | 0.62 | 8.00 |
| 4 | Other nondurable goods[f] | 0.089 | 0.60 | 0.49 |
| Services | | 0.730[g] | 0.63[h] | 0.61[h] |
| 5 | Housing and utilities | 0.208 | 0.74 | 0.32 |
| 6 | Health care | 0.166 | 0.93 | 0.57 |
| 7 | Transportation services | 0.038 | 0.60 | 0.59 |
| 8 | Recreation services | 0.041 | 0.74 | 0.37 |
| 9 | Food services and accommodations | 0.072 | 0.74 | 0.28 |
| 10 | Financial services and insurance | 0.084 | 0.58 | 1.11 |
| 11 | Other services[i] | 0.095 | 0.77 | 0.34 |
| 12 | Final consumption expenditures of nonprofit institutions serving households (NPISHs) | 0.026 | –0.08 | 1.27 |

[a] Sectors are identified mostly by third-level disaggregate categories underlying PCE in Table 2.3.5 of the National Income and Product Accounts published by the US BEA, excluding those for durable goods.

[b] The average shares are computed as the proportions of sectoral PCE in total PCE on all nondurables and services, averaged over the sample period of 1985Q1–2015Q4.

[c] Sectoral inflation rates are computed as the first differences of the logarithm of quarterly sectoral PCE price indices. Both the means and the standard deviations are taken over the sample period of 1985Q1–2015Q4 with the respective quarterly series.

[d] Sum of the corresponding items in sectors 1–4.

[e] Average of the corresponding items in sectors 1–4.

[f] This category includes pharmaceutical and other medical products; recreational items; household supplies; personal care products; tobacco; magazines, newspapers, and stationery; and net expenditures abroad by US residents.

[g] Sum of the corresponding items in sectors 5–12.

[h] Average of the corresponding items in sectors 5–12.

[i] This category includes communication; education services; professional and other services; personal care and clothing services; social services and religious activities; household maintenance; and net foreign travel.

**Table 2** Calibrated parameters

| Parameter | Description | Value |
|---|---|---|
| $\gamma$ | Growth rate along the balanced growth path | 1.0046 |
| $\overline{\pi}$ | Steady-state inflation rate | 1.0062 |
| $\overline{g}$ | Steady-state share of government spending in GDP | 0.17 |
| $\sigma_c$ | Inverse of intertemporal elasticity of substitution | 1.25 |
| $\beta$ | Subjective discount factor | 0.9987 |
| $\overline{L}$ | Steady-state labor supply | 1 |
| $\sigma_l$ | Inverse of Frisch elasticity of labor supply | 2 |
| $\delta$ | Depreciation rate of capital | 0.025 |
| $\alpha$ | Exponent of capital in the production function | 0.33 |
| $\psi$ | Ratio of weighted average of sectoral fix costs to steady-state output ($\psi = \sum_{s=1}^{S} \omega_s \Psi_s / \overline{y}$) | 0.04 |
| $\bar{\epsilon}^w$ | Steady-state wage markup | 0.05 |
| $\{\bar{\epsilon}^p(s)\}_{s=1}^S$ | Steady-state sectoral price markups | 0.2 |
| $\nu$ | Inverse of intersectoral elasticity of substitution | 2.5 |
| $\{\omega_s^{\text{ob}}\}_{s=1}^S$ | Observable sizes of sectors | See Table 1 |
| $\text{var}(\eta_t^{\text{me},x})$ | Variances of measurement errors | |
| | $x_t = \Delta \ln y_t, \Delta \ln c_t, \Delta \ln i_t, \pi_t, \pi_t(1), \ldots, \pi_t(S)$ | $0.05\,\text{var}(100 x_t^{\text{data}})$ |
| | $x_t = \Delta \ln L_t, \Delta \ln w_t, R_t/100$ | $0.1\,\text{var}(100 x_t^{\text{data}})$ |

*Note*. The time unit of the model is a quarter. Other calibrated parameters include the steady states of the (unscaled) exogenous shocks or innovations, $\bar{\epsilon}^b = \bar{\epsilon}^i = \bar{\epsilon}^a = \bar{\zeta}^p = \bar{\epsilon}^r = 1$, and the scaling parameter $\zeta^p = 10$.

**Table 3** Comparison of selected steady-state variables in the model and the data

| Variable | Model | Data[a] |
|---|---|---|
| Consumption–GDP ratio ($\bar{c}/\bar{y}$) | 0.57 | 0.57[b] |
| Investment–GDP ratio ($\bar{i}/\bar{y}$) | 0.26 | 0.26[c] |
| Capital stock–GDP ratio ($\bar{k}/\bar{y}$) | 8.9 | 10.6[d] |
| Interest rate, annual percentage rate ($100(\overline{R}^4 - 1)$) | 5.43 | 5.41[e] |
| Inflation, annual percentage rate ($100(\overline{\pi}^4 - 1)$) | 2.50 | 3.00[f] |

[a] Values in this column are sample averages over the period of 1985Q1–2008Q2 unless otherwise noted. See the appendix for details on the sources of data and the transformations applied.

[b] Consumption includes PCE on nondurables and services.

[c] Investment includes gross private domestic investment and PCE on durables.

[d] Capital stock includes (net stock of) private fixed assets (nonresidential and residential), (net stock of) consumer durable goods, and (stock of) private inventories. This value is computed with annual time series over 1985–2007.

[e] The interest rate is the daily effective federal funds rate on the last business day of the preceding quarter.

[f] Inflation is the first difference of the logarithm of a price index measuring the overall price level of PCE on nondurables and services. The price index is the ratio of total current-dollar PCE on nondurables and services to total chained-dollar PCE in the two categories. Inflation rates are first computed on a quarterly basis and averaged over the period of 1985Q1–2008Q2. The resulting average quarterly rate is then converted to the annual percentage rate.

**Table 4** Priors and posteriors of the estimated parameters: non-sector-specific parameters

| Parameter and description | | Prior distribution[a] | | | Posterior distribution | | | |
|---|---|---|---|---|---|---|---|---|
| | | $\mathcal{M}_1$ & $\mathcal{M}_2$ | | | $\mathcal{M}_1$ | | $\mathcal{M}_2$ | |
| | | Type[b] | Mean | SD | Mode | SD | Mode | SD |
| A. Structural parameters | | | | | | | | |
| $h$ | Habit parameter | B | 0.7 | 0.1 | 0.86 | 0.02 | 0.79 | 0.02 |
| $\kappa_z$ | Curvature of utilization cost | B | 0.5 | 0.15 | 0.91 | 0.04 | 0.94 | 0.03 |
| $\kappa_i$ | Curvature of investment adj. cost | B | 0.8 | 0.1 | 0.92 | 0.02 | 0.88 | 0.03 |
| $\theta_w$ | Calvo wage stickiness | B | 0.75 | 0.1 | 0.65 | 0.04 | 0.59 | 0.04 |
| $\iota_w$ | Degree of wage indexation | B | 0.5 | 0.15 | 0.15 | 0.07 | 0.20 | 0.08 |
| B. Monetary policy parameters | | | | | | | | |
| $\rho_r$ | Policy smoothing parameter | B | 0.75 | 0.1 | 0.72 | 0.04 | 0.57 | 0.05 |
| $\rho_\pi$ | Strength of resp. to agg. inflation ($\mathcal{M}_1$)[c] | N | 1.75 | 0.2 | 1.59 | 0.19 | — | — |
| $\rho_\pi^*$ | Strength of overall resp. to inflation ($\mathcal{M}_2$)[c] | N | 1.75 | 0.2 | — | — | 2.07 | 0.14 |
| $\rho_x$ | Strength of response to output gap | N | 0.125 | 0.05 | 0.25 | 0.03 | 0.14 | 0.03 |
| C. Persistence of shocks | | | | | | | | |
| $\rho_b$ | Risk premium | B | 0.5 | 0.2 | 0.22 | 0.09 | 0.17 | 0.08 |
| $\rho_i$ | Marginal efficiency of investment | B | 0.5 | 0.2 | 0.87 | 0.03 | 0.80 | 0.04 |
| $\rho_a$ | Total factor productivity | B | 0.5 | 0.2 | 0.98 | 0.01 | 0.98 | 0.01 |
| $\rho_w$ | Wage markup | B | 0.5 | 0.2 | 0.04 | 0.03 | 0.04 | 0.03 |
| $\rho_p$ | Price markup: common component | B | 0.5 | 0.2 | 0.15 | 0.12 | 0.11 | 0.08 |
| $\rho_g$ | Government spending | B | 0.5 | 0.2 | 0.63 | 0.13 | 0.46 | 0.15 |
| $\rho_{ga}$ | Productivity on government spending | B | 0.5 | 0.2 | 0.35 | 0.04 | 0.31 | 0.04 |
| D. Standard deviations of innovations[d] | | | | | | | | |
| $100\tilde{\sigma}_b$ | Risk premium | IG | 0.2 | 0.33 | 0.11 | 0.01 | 0.11 | 0.01 |
| $100\tilde{\sigma}_i$ | Marginal efficiency of investment | IG | 0.2 | 0.33 | 0.29 | 0.03 | 0.34 | 0.03 |
| $100\sigma_a$ | Total factor productivity | IG | 0.2 | 0.33 | 0.40 | 0.02 | 0.40 | 0.02 |
| $100\tilde{\sigma}_w$ | Wage markup | IG | 0.2 | 0.33 | 0.41 | 0.03 | 0.42 | 0.03 |
| $100\tilde{\sigma}_p$ | Price markup: common component | IG | 0.2 | 0.33 | 0.34 | 0.10 | 0.28 | 0.06 |
| $100\sigma_g$ | Government spending | IG | 0.2 | 0.33 | 0.12 | 0.02 | 0.11 | 0.02 |
| $100\sigma_r$ | Monetary policy | IG | 0.2 | 0.33 | 0.29 | 0.02 | 0.28 | 0.02 |
| Marginal log-likelihood[e] | | | | | –2,035.34 | | –2,019.04 | |

[a] Endogenous priors à la Christiano et al. (2011) used in estimation. The priors specified here are the initial priors.
[b] "B" stands for a beta distribution, "N" for a normal distribution, and "IG" for an inverse Gamma distribution (type 2).
[c] The prior is truncated at 1.0001 without redistributing the remaining density.
[d] A symbol with a tilde (˜) accent denotes the standard deviation of the scaled innovation. See the appendix for details about scaling of shocks and innovations.
[e] Laplace approximation.

**Table 5** Priors and posteriors of the estimated parameters: sector-specific monetary policy parameters ($\mathscr{M}_2$ only)

| $s$ | Sector name | Prior distribution[a] | | | Posterior distribution | | | |
|---|---|---|---|---|---|---|---|---|
| | | $\rho_\pi^{**}(s)$ | | | $\rho_\pi^{**}(s)$ | | $\rho_\pi^{*}(s)$ | |
| | | Type[b] | Mean | SD | Mode | SD | Mode[c] | SD[d] |
| Strength of responses to sectoral inflation, $\rho_\pi^{**}(s)$ & $\rho_\pi^{*}(s)$ ($\mathscr{M}_2$ only) | | | | | | | | |
| 1 | Food and beverages p.f.o.p.c. | N | 0.0 | 0.5 | −0.04 | 0.39 | 0.094 | 0.039 |
| 2 | Clothing and footwear | N | 0.0 | 0.5 | 0.08 | 0.44 | 0.052 | 0.021 |
| 3 | Gasoline and other energy goods | N | 0.0 | 0.5 | −0.94 | 0.11 | 0.002 | 0.004 |
| 4 | Other nondurable goods | N | 0.0 | 0.5 | 0.35 | 0.40 | 0.121 | 0.036 |
| 5 | Housing and utilities | N | 0.0 | 0.5 | 0.59 | 0.33 | 0.332 | 0.069 |
| 6 | Health care | N | 0.0 | 0.5 | −1.00 | 0.25 | 0.000 | 0.042 |
| 7 | Transportation services | — | — | — | 0.84[e] | 1.42[e] | 0.070 | 0.054 |
| 8 | Recreation Services | N | 0.0 | 0.5 | 0.18 | 0.49 | 0.048 | 0.020 |
| 9 | Food services and accommodations | N | 0.0 | 0.5 | 0.38 | 0.48 | 0.100 | 0.035 |
| 10 | Financial services and insurance | N | 0.0 | 0.5 | −0.41 | 0.28 | 0.050 | 0.024 |
| 11 | Other services | N | 0.0 | 0.5 | 0.08 | 0.44 | 0.103 | 0.042 |
| 12 | Final consumption expenditures of NPISHs | N | 0.0 | 0.5 | 0.13 | 0.44 | 0.030 | 0.012 |

[a] Endogenous priors à la Christiano et al. (2011) used in estimation. The priors specified here are the initial priors.
[b] "N" stands for a normal distribution.
[c] Inferred from the corresponding posterior modes of $\{\rho_\pi^{**}(s)\}_{s=1}^{S}$.
[d] Inferred from the corresponding posterior standard deviations of $\{\rho_\pi^{**}(s)\}_{s=1}^{S}$.
[e] The posterior mode of $\rho_\pi^{**}(7)$ is not directly estimated but inferred from posterior mode estimates of other $\rho_\pi^{**}(s)$ and the restriction (10). The posterior standard deviation of $\rho_\pi^{**}(7)$ is inferred from the other direct estimates.

**Table 6** Priors and posteriors of the estimated parameters: sector-specific structural parameters

| | Calvo price stickiness $\theta_p(s)$ | | | | | | | Degree of price indexation $\iota_p(s)$ | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Prior distribution[a] | | | Posterior distribution | | | | Prior distribution[a] | | | Posterior distribution | | | |
| | $\mathcal{M}_1$ & $\mathcal{M}_2$ | | | $\mathcal{M}_1$ | | $\mathcal{M}_2$ | | $\mathcal{M}_1$ & $\mathcal{M}_2$ | | | $\mathcal{M}_1$ | | $\mathcal{M}_2$ | |
| $s$ | Type[b] | Mean | SD | Mode | SD | Mode | SD | Type[b] | Mean | SD | Mode | SD | Mode | SD |
| 1 | B | 0.5 | 0.125 | 0.800 | 0.045 | 0.725 | 0.033 | B | 0.5 | 0.15 | 0.29 | 0.10 | 0.36 | 0.11 |
| 2 | B | 0.5 | 0.125 | 0.944 | 0.020 | 0.941 | 0.019 | B | 0.5 | 0.15 | 0.19 | 0.08 | 0.18 | 0.08 |
| 3 | B | 0.5 | 0.125 | 0.446 | 0.091 | 0.417 | 0.076 | B | 0.5 | 0.15 | 0.50 | 0.18 | 0.49 | 0.18 |
| 4 | B | 0.5 | 0.125 | 0.926 | 0.018 | 0.900 | 0.023 | B | 0.5 | 0.15 | 0.11 | 0.05 | 0.11 | 0.05 |
| 5 | B | 0.5 | 0.125 | 0.908 | 0.018 | 0.873 | 0.018 | B | 0.5 | 0.15 | 0.14 | 0.04 | 0.15 | 0.05 |
| 6 | B | 0.5 | 0.125 | 0.950 | 0.014 | 0.949 | 0.013 | B | 0.5 | 0.15 | 0.11 | 0.04 | 0.11 | 0.04 |
| 7 | B | 0.5 | 0.125 | 0.906 | 0.020 | 0.907 | 0.024 | B | 0.5 | 0.15 | 0.29 | 0.10 | 0.30 | 0.10 |
| 8 | B | 0.5 | 0.125 | 0.932 | 0.015 | 0.893 | 0.033 | B | 0.5 | 0.15 | 0.15 | 0.06 | 0.13 | 0.05 |
| 9 | B | 0.5 | 0.125 | 0.899 | 0.014 | 0.901 | 0.025 | B | 0.5 | 0.15 | 0.15 | 0.04 | 0.17 | 0.04 |
| 10 | B | 0.5 | 0.125 | 0.877 | 0.047 | 0.876 | 0.046 | B | 0.5 | 0.15 | 0.41 | 0.15 | 0.40 | 0.15 |
| 11 | B | 0.5 | 0.125 | 0.945 | 0.013 | 0.925 | 0.015 | B | 0.5 | 0.15 | 0.26 | 0.06 | 0.27 | 0.06 |
| 12 | B | 0.5 | 0.125 | 0.714 | 0.037 | 0.721 | 0.036 | B | 0.5 | 0.15 | 0.39 | 0.14 | 0.38 | 0.14 |

[a] Endogenous priors à la Christiano et al. (2011) used in estimation. The priors specified here are the initial priors.
[b] "B" stands for a beta distribution.

**Table 7** Priors and posteriors of the estimated parameters: parameters of the sector-specific markup shocks

| | Shock persistence $\rho_p(s)$ | | | | | | | Standard deviation of scaled innovation $100\tilde{\sigma}_p(s)$[a] | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Prior distribution[b] | | | Posterior distribution | | | | Prior distribution[b] | | | Posterior distribution | | | |
| | $\mathscr{M}_1$ & $\mathscr{M}_2$ | | | $\mathscr{M}_1$ | | $\mathscr{M}_2$ | | $\mathscr{M}_1$ & $\mathscr{M}_2$ | | | $\mathscr{M}_1$ | | $\mathscr{M}_2$ | |
| $s$ | Type[c] | Mean | SD | Mode | SD | Mode | SD | Type[c] | Mean | SD | Mode | SD | Mode | SD |
| 1 | B | 0.5 | 0.2 | 0.67 | 0.15 | 0.89 | 0.07 | IG | 0.2 | 0.33 | 0.22 | 0.06 | 0.15 | 0.03 |
| 2 | B | 0.5 | 0.2 | 0.34 | 0.09 | 0.36 | 0.09 | IG | 0.2 | 0.33 | 0.47 | 0.07 | 0.47 | 0.07 |
| 3 | B | 0.5 | 0.2 | 0.81 | 0.08 | 0.86 | 0.05 | IG | 4.0 | 6.67 | 11.2 | 3.3 | 11.9 | 3.3 |
| 4 | B | 0.5 | 0.2 | 0.56 | 0.08 | 0.62 | 0.08 | IG | 0.2 | 0.33 | 0.19 | 0.03 | 0.18 | 0.03 |
| 5 | B | 0.5 | 0.2 | 0.62 | 0.08 | 0.57 | 0.11 | IG | 0.2 | 0.33 | 0.092 | 0.018 | 0.10 | 0.022 |
| 6 | B | 0.5 | 0.2 | 0.93 | 0.02 | 0.95 | 0.01 | IG | 0.1 | 0.33 | 0.027 | 0.005 | 0.022 | 0.005 |
| 7 | B | 0.5 | 0.2 | 0.24 | 0.09 | 0.27 | 0.09 | IG | 0.2 | 0.33 | 0.44 | 0.05 | 0.44 | 0.05 |
| 8 | B | 0.5 | 0.2 | 0.30 | 0.10 | 0.34 | 0.13 | IG | 0.2 | 0.33 | 0.22 | 0.03 | 0.22 | 0.04 |
| 9 | B | 0.5 | 0.2 | 0.32 | 0.11 | 0.44 | 0.17 | IG | 0.2 | 0.33 | 0.12 | 0.02 | 0.11 | 0.03 |
| 10 | B | 0.5 | 0.2 | 0.49 | 0.11 | 0.50 | 0.11 | IG | 0.2 | 0.33 | 0.73 | 0.12 | 0.70 | 0.11 |
| 11 | B | 0.5 | 0.2 | 0.40 | 0.08 | 0.43 | 0.09 | IG | 0.2 | 0.33 | 0.17 | 0.02 | 0.17 | 0.03 |
| 12 | B | 0.5 | 0.2 | 0.97 | 0.01 | 0.97 | 0.01 | IG | 0.2 | 0.33 | 0.32 | 0.06 | 0.33 | 0.06 |

[a] The tilde (˜) accent denotes that the standard deviation is of the scaled innovation. See the appendix for details about scaling of shocks and innovations.
[b] Endogenous priors à la Christiano et al. (2011) used in estimation. The priors specified here are the initial priors.
[c] "B" stands for a beta distribution and "IG" for an inverse gamma distribution (type 2).

**Table 8** Comparison of estimated sectoral price stickiness at the posterior mode ($\mathscr{M}_2$) and average infrequencies of price change from the micro data

| | | Estimated ($\mathscr{M}_2$) | | Micro-data[a] | |
|---|---|---|---|---|---|
| $s$ | Sector name | Posterior Mode | Rank[b] | Statistic | Rank |
| 1 | Food and beverages p.f.o.p.c. | 0.725 | 10 | 0.689 | 9 |
| 2 | Clothing and footwear | 0.941 | 2 | 0.692 | 8 |
| 3 | Gasoline and other energy goods | 0.417 | 11 | 0.148 | 11 |
| 4 | Other nondurable goods | 0.900 | 6 | 0.815 | 6 |
| 5 | Housing and utilities | 0.873 | 9 | 0.596 | 10 |
| 6 | Health care | 0.949 | 1 | 0.95 | 1 |
| 7 | Transportation services | 0.907 | 4 | 0.721 | 7 |
| 8 | Recreation Services | 0.893 | 7 | 0.899 | 3 |
| 9 | Food services and accommodations | 0.901 | 5 | 0.843 | 5 |
| 10 | Financial services and insurance | 0.876 | 8 | 0.921 | 2 |
| 11 | Other services | 0.925 | 3 | 0.864 | 4 |
| 12 | Final consumption expenditures of NPISHs | 0.721 | | — | |

[a] These are average monthly "infrequencies" of price change in the sectors, reported in Carvalho and Lee (2011, Table 16). Carvalho and Lee matched Bils and Klenow's (2004) micro data on the frequency of price change to disaggregate PCE categories. Their 15-sector specification consisted of sectors matching the ones used in this paper.

[b] Only the estimated sectoral price stickiness in the first 11 sectors are ranked.

**Table 9** Standard deviations of the unscaled innovations underlying the sector-specific components of the price markup shocks and decomposition of standard deviations of the unscaled sectoral price markup shocks at the posterior mode ($\mathscr{M}_2$)

| | Innovation components | | Shock components | | |
|---|---|---|---|---|---|
| | Common | Sector-specific | Common | Sector-specific | Total |
| $s$ | $100\,\mathrm{sd}(\eta_t^p)$ | $100\,\mathrm{sd}(\eta_t^p(s))$ | $100\,\mathrm{sd}(\hat{\zeta}_t^p)$ | $100\,\mathrm{sd}(\hat{\zeta}_t^p(s))$ | $100\,\mathrm{sd}(\hat{\epsilon}_t^p(s))$ |
| 1 | 2.79 | 1.42 | 2.81 | 3.13 | 5.94 |
| 2 | 2.79 | 120.1 | 2.81 | 128.7 | 131.5 |
| 3 | 2.79 | 14.6 | 2.81 | 28.9 | 31.7 |
| 4 | 2.79 | 15.9 | 2.81 | 20.2 | 23.0 |
| 5 | 2.79 | 5.59 | 2.81 | 6.79 | 9.60 |
| 6 | 2.79 | 7.64 | 2.81 | 25.3 | 28.1 |
| 7 | 2.79 | 44.9 | 2.81 | 46.6 | 49.4 |
| 8 | 2.79 | 16.7 | 2.81 | 17.7 | 20.5 |
| 9 | 2.79 | 10.1 | 2.81 | 11.3 | 14.1 |
| 10 | 2.79 | 39.7 | 2.81 | 45.8 | 48.6 |
| 11 | 2.79 | 26.5 | 2.81 | 29.4 | 32.2 |
| 12 | 2.79 | 3.03 | 2.81 | 13.4 | 16.2 |

*Note*. The (log-linearized) unscaled sector-$s$ ($s = 1, \ldots, S$) price markup shock $\hat{\epsilon}_t^p(s)$ is the sum of a common component, $\hat{\zeta}_t^p$, and a sector-specific component, $\hat{\zeta}_t^p(s)$: $\hat{\epsilon}_t^p(s) = \hat{\zeta}_t^p + \hat{\zeta}_t^p(s)$. The common component $\hat{\zeta}_t^p$ follows a first-order autoregression (AR(1)) with a normally and independently distributed (NID) innovation: $\hat{\zeta}_t^p = \rho_p \hat{\zeta}_{t-1}^p + \eta_t^p$, $\eta_t^p \sim \mathrm{NID}(0, \sigma_p^2)$. Each sector-specific component $\hat{\zeta}_t^p(s)$ follows an AR(1) with an NID innovation: $\hat{\zeta}_t^p(s) = \rho_p(s)\hat{\zeta}_{t-1}^p(s) + \eta_t^p(s)$, $\eta_t^p(s) \sim \mathrm{NID}(0, \sigma_p^2(s))$.

**Table 10** Comparison of standard deviations of the observed data (in percent) and standard deviations of the corresponding observable variables in the estimated model at the posterior mode ($\mathscr{M}_2$)

| Aggregates | | Data sd[a] Point estimate | Data sd[a] 95% confidence interval[b] | Model sd[c] |
|---|---|---|---|---|
| $\Delta y_t$ | Growth of real GDP per capita | 0.60 | [0.51, 0.78] | 0.64 |
| $\Delta c_t$ | Growth of real consumption per capita | 0.42 | [0.37, 0.48] | 0.44 |
| $\Delta i_t$ | Growth of real investment per capita | 2.27 | [1.90, 2.88] | 1.93 |
| $\Delta L_t$ | Growth of labor supply per capita | 0.72 | [0.60, 0.88] | 0.82 |
| $\Delta w_t$ | Growth of real wage | 0.87 | [0.75, 1.05] | 0.85 |
| $\Delta R_t$ | Growth of nominal interest rate | 0.34 | [0.25, 0.50] | 0.37 |
| $\pi_t$ | Aggregate inflation | 0.40 | [0.33, 0.57] | 0.44 |

Sectoral inflation rates

| | Data sd[a] Point estimate | Data sd[a] 95% confidence interval[b] | Model sd[c] | | Data sd[a] Point estimate | Data sd[a] 95% confidence interval[b] | Model sd[c] |
|---|---|---|---|---|---|---|---|
| $\pi_t(1)$ | 0.54 | [0.47, 0.64] | 0.61 | $\pi_t(7)$ | 0.59 | [0.53, 0.70] | 0.60 |
| $\pi_t(2)$ | 0.73 | [0.65, 0.84] | 0.74 | $\pi_t(8)$ | 0.37 | [0.32, 0.43] | 0.37 |
| $\pi_t(3)$ | 8.00 | [6.50, 10.88] | 8.51 | $\pi_t(9)$ | 0.28 | [0.25, 0.31] | 0.29 |
| $\pi_t(4)$ | 0.49 | [0.42, 0.59] | 0.49 | $\pi_t(10)$ | 1.11 | [0.91, 1.41] | 1.27 |
| $\pi_t(5)$ | 0.32 | [0.27, 0.37] | 0.33 | $\pi_t(11)$ | 0.34 | [0.30, 0.38] | 0.35 |
| $\pi_t(6)$ | 0.57 | [0.51, 0.64] | 0.54 | $\pi_t(12)$ | 1.27 | [1.12, 1.44] | 1.20 |

[a] See Section 4.1 for descriptions of the data and variable definitions. Standard deviations are computed for the observed quarterly time series spanning 1985Q1–2015Q4.
[b] Bootstrapped with the bias-corrected and accelerated method.
[c] Unconditional standard deviations with measurement errors taken into consideration.

**Table 11** Variance decomposition (in percent) at the posterior mode at the infinite horizon ($\mathscr{M}_2$)

| | Shock / Innovation[a] | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | $\eta_t^p(s),\ s = 1, \ldots, S$ | | | | | | | | | | | |
| Variable | $\eta_t^b$ | $\eta_t^i$ | $\eta_t^a$ | $\eta_t^w$ | $\eta_t^g$ | $\eta_t^r$ | $\eta_t^p$ | AGG | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| $\hat{y}_t$ Output | 0.5 | 58.1 | 34.9 | 1.3 | 0.1 | 0.3 | 0.0 | 95.2 | 0.1 | 0.0 | 0.6 | 0.1 | 0.1 | 3.7 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.2 |
| $\hat{c}_t$ Consumption | 1.2 | 51.5 | 39.5 | 2.9 | 0.0 | 0.6 | 0.0 | 95.9 | 0.1 | 0.0 | 0.7 | 0.1 | 0.1 | 2.8 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.1 |
| $\hat{\imath}_t$ Investment | 0.1 | 76.9 | 18.0 | 0.2 | 0.0 | 0.0 | 0.0 | 95.1 | 0.0 | 0.0 | 0.2 | 0.0 | 0.0 | 4.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 |
| $\hat{L}_t$ Labor supply | 2.0 | 81.8 | 2.5 | 5.3 | 0.4 | 1.2 | 0.1 | 93.2 | 0.2 | 0.1 | 1.9 | 0.2 | 0.2 | 3.5 | 0.0 | 0.0 | 0.0 | 0.3 | 0.0 | 0.4 |
| $\hat{w}_t$ Real wage | 0.0 | 30.1 | 32.0 | 11.9 | 0.0 | 0.0 | 0.1 | 74.1 | 0.2 | 0.1 | 4.4 | 0.2 | 0.1 | 19.5 | 0.0 | 0.0 | 0.0 | 0.7 | 0.1 | 0.7 |
| $\hat{R}_t$ Interest rate | 1.1 | 45.3 | 6.9 | 9.0 | 0.1 | 22.4 | 1.3 | 86.0 | 0.9 | 0.6 | 2.8 | 1.5 | 2.4 | 1.9 | 0.5 | 0.1 | 0.2 | 2.2 | 0.4 | 0.6 |
| $\hat{\pi}_t$ Agg. inflation | 0.1 | 8.9 | 3.8 | 9.4 | 0.0 | 0.1 | 4.6 | 27.1 | 1.0 | 0.7 | 51.1 | 1.1 | 1.3 | 9.5 | 0.3 | 0.1 | 0.1 | 6.6 | 0.4 | 0.7 |
| Sectoral inflation rates $\hat{\pi}_t(s),\ s = 1, \ldots, S$ | | | | | | | | | | | | | | | | | | | | |
| $s = 1$ | 0.3 | 14.1 | 6.0 | 16.0 | 0.0 | 0.2 | 15.5 | 52.4 | 42.8 | 0.1 | 2.0 | 0.1 | 0.1 | 2.0 | 0.0 | 0.0 | 0.0 | 0.3 | 0.0 | 0.2 |
| $s = 2$ | 0.0 | 1.1 | 0.7 | 1.5 | 0.0 | 0.0 | 0.1 | 3.5 | 0.0 | 94.4 | 0.7 | 0.0 | 0.1 | 1.3 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.1 |
| $s = 3$ | 0.0 | 0.1 | 0.1 | 0.3 | 0.0 | 0.0 | 1.8 | 2.3 | 0.0 | 0.0 | 97.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| $s = 4$ | 0.1 | 5.5 | 2.3 | 5.7 | 0.0 | 0.1 | 0.5 | 14.2 | 0.1 | 0.0 | 0.5 | 81.8 | 0.1 | 2.9 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.2 |
| $s = 5$ | 0.2 | 18.9 | 6.9 | 18.0 | 0.0 | 0.3 | 2.9 | 47.1 | 0.2 | 0.1 | 1.8 | 0.2 | 42.9 | 6.7 | 0.1 | 0.0 | 0.0 | 0.4 | 0.1 | 0.5 |
| $s = 6$ | 0.0 | 1.3 | 1.2 | 2.2 | 0.0 | 0.0 | 0.1 | 4.8 | 0.0 | 0.0 | 0.4 | 0.1 | 0.1 | 94.4 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.2 |
| $s = 7$ | 0.1 | 4.1 | 1.7 | 4.1 | 0.0 | 0.1 | 0.5 | 10.4 | 0.1 | 0.1 | 2.2 | 0.1 | 0.1 | 2.1 | 84.5 | 0.0 | 0.0 | 0.3 | 0.0 | 0.2 |
| $s = 8$ | 0.2 | 11.1 | 4.4 | 11.1 | 0.0 | 0.2 | 1.2 | 28.2 | 0.1 | 0.1 | 1.1 | 0.2 | 0.2 | 5.2 | 0.0 | 64.2 | 0.0 | 0.2 | 0.0 | 0.4 |
| $s = 9$ | 0.2 | 17.1 | 7.0 | 17.3 | 0.0 | 0.3 | 1.7 | 43.5 | 0.2 | 0.1 | 2.9 | 0.3 | 0.4 | 8.7 | 0.1 | 0.0 | 42.6 | 0.5 | 0.1 | 0.6 |
| $s = 10$ | 0.0 | 1.4 | 0.5 | 1.3 | 0.0 | 0.0 | 0.2 | 3.5 | 0.0 | 0.0 | 0.8 | 0.0 | 0.0 | 0.5 | 0.0 | 0.0 | 0.0 | 95.1 | 0.0 | 0.0 |
| $s = 11$ | 0.1 | 8.3 | 4.0 | 9.2 | 0.0 | 0.1 | 0.9 | 22.6 | 0.2 | 0.1 | 5.2 | 0.2 | 0.3 | 5.9 | 0.1 | 0.0 | 0.0 | 0.8 | 64.2 | 0.4 |
| $s = 12$ | 0.1 | 3.7 | 1.6 | 4.2 | 0.0 | 0.1 | 4.3 | 13.9 | 0.0 | 0.0 | 0.6 | 0.0 | 0.0 | 0.5 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 84.8 |

[a] $\eta_t^b$ is the risk premium innovation, $\eta_t^i$ is the innovation to marginal efficiency of investment, $\eta_t^a$ is the innovation to total factor productivity, $\eta_t^w$ is the wage markup innovation, $\eta_t^g$ is the government spending innovation, $\eta_t^r$ is the monetary policy innovation, $\eta_t^p$ is the innovation underlying the common component of the sectoral price markup shocks, and $\eta_t^p(s)$ ($s = 1, \ldots, S$) is the innovation underlying the sector-specific component of the sector-$s$ price markup shock. The numbers in the column "AGG" are the total fractions of unconditional forecast error variances of the corresponding variables explained by non-sector-specific, aggregate shocks.

**Table 12** Regression analysis of the cross-sectional relationship between responsiveness of the sectoral relative price or its growth to a monetary policy shock and sectoral characteristics in price flexibility or dynamic price indexation at the posterior mode ($\mathscr{M}_2$)

| Dependent variable | Sample exclusion[a] | Coefficients of interest[b] $-\theta_p^*(s)$ | | $\iota_p^*(s)$ | | $R^2$ |
|---|---|---|---|---|---|---|
| Response of sectoral relative price [$\hat{\varphi}_t(s)$] | | | | | | |
| Signed maximum [$-\mathrm{IRF}^m(\hat{\varphi}(s), \eta^r)$] | — | 2.04** | (0.15) | 0.39** | (0.12) | 0.99 |
| Cumulative [$-\mathrm{IRF}^c(\hat{\varphi}(s), \eta^r)$] | — | 23.83** | (7.86) | 5.30 | (6.32) | 0.88 |
| Response of growth of sectoral relative price [$\Delta\hat{\varphi}_t(s)$] | | | | | | |
| Signed maximum [$-\mathrm{IRF}^m(\Delta\hat{\varphi}(s), \eta^r)$] | — | 0.98** | (0.14) | −0.02 | (0.10) | 0.97 |
| Cumulative [$-\mathrm{IRF}^c(\Delta\hat{\varphi}(s), \eta^r)$] | — | 0.07 | (0.10) | 0.02 | (0.09) | 0.33 |
| Cumulative [$-\mathrm{IRF}^c(\Delta\hat{\varphi}(s), \eta^r)$] | 5, 7, 16 | 0.43** | (0.21) | 0.02 | (0.19) | 0.93 |

*Note*. The dependent variable in each regression is equivalent to the corresponding response to a one-standard-deviation, expansionary monetary policy shock. Each regression also includes the sector size ($\omega_s$) as a control variable and a constant. The number of observations in each regression is 12 unless otherwise noted. The starred variables are transformed versions of the corresponding unstarred variables with the transformation function $f(x) = \ln[x/(1-x)]$ applied. See the text for variable definitions.

[a] The sectors whose data points are excluded from the regression sample are listed.

[b] Bootstrapped standard errors in parentheses.

** Significant at 5%.

**Table 13** Welfare comparison between the baseline monetary policy and alternatively randomly parameterized policy schemes

| | $\delta_c^{\approx}$ (percent) | Difference from baseline (percentage points) | $\delta_c^{\approx}$ (percent) | Difference from baseline (percentage points) |
|---|---|---|---|---|
| Baseline ($\mathscr{R}_0$) | –0.896 | | | |
| Targeting aggregate inflation | –0.994 | –0.097 | | |
| | Experiment 1 (random draw): Welfare improved in 0 out of 100 trials | | Experiment 2 (random perturbation): Welfare improved in 45 out of 100 trials | |
| Average | –1.097 | –0.200 | –0.901 | –0.005 |
| Median | –1.043 | –0.146 | –0.900 | –0.004 |
| Maximum | –0.907 | –0.010 | –0.868 | 0.028 |
| Minimum | –1.852 | –0.956 | –0.942 | –0.046 |
| SD | 0.172 | | 0.019 | |

**Table 14** Optimal composition of the target index of inflation in the two cases

| | | Case ($d$) | |
|---|---|---|---|
| | | 1 (constrained)[a] | 2 (unconstrained)[b] |
| Welfare | | | |
| $\delta_c^{\approx}(\mathscr{R}_d^*)$ | | −0.837 | −0.754 |
| $\delta_c^{\approx}(\mathscr{R}_d^*) - \delta_c^{\approx}(\mathscr{R}_0)$ | | 0.059 | 0.142 |
| Optimal parameter values | | | |
| Sectoral weights $\rho_\pi^*(s;\mathscr{R}_d^*)$ | | | |
| 1 | Food and beverages p.f.o.p.c. | 0.511 | 0.566 |
| 2 | Clothing and footwear | 0 | −0.349 |
| 3 | Gasoline and other energy goods | 0.010 | 0.010 |
| 4 | Other nondurable goods | 0 | −0.008 |
| 5 | Housing and utilities | 0.406 | 1.230 |
| 6 | Health care | 0 | −0.237 |
| 7 | Transportation services | 0 | 0.073 |
| 8 | Recreation services | 0 | −0.368 |
| 9 | Food services and accommodations | 0 | 0.045 |
| 10 | Financial services and insurance | 0.052 | 0.072 |
| 11 | Other services | 0 | −0.800 |
| 12 | Final consumption expenditure of NPISHs | 0.021 | 0.028 |

[a] The weights of sectoral inflations in the inflation index are constrained between zero and one, i.e., $\rho_\pi^*(s;\mathscr{R}) \in [0, 1]$, $s = 1, \dots, S$. The sectoral weights sum to one, i.e., $\sum_{s=1}^{S} \rho_\pi^*(s;\mathscr{R}) = 1$.

[b] The sectoral weights sum to one, i.e., $\sum_{s=1}^{S} \rho_\pi^*(s;\mathscr{R}) = 1$.

**Table 15** Welfare evaluation of adjusting the strength of response to overall inflation or the output gap at the posterior mode ($\mathcal{M}_2$)

| | $\delta_c^{\approx}$ (percent) | Difference from baseline (percentage points) |
|---|---|---|
| Baseline ($\rho_\pi^* = 2.07$, $\rho_x = 0.140$) | –0.896 | |
| Flexible-wage-and-price economy with the wage mark up and the price markup shocks shut down ($\theta_w = \theta_p(s) = 0$, $\epsilon_t^w = \bar{\epsilon}^w$, $\epsilon_t^p(s) = \bar{\epsilon}^p(s)$, $\forall s = 1, \ldots, S$, $\forall t = 0, 1, \ldots$) | –0.120 | 0.776 |
| Adjusted strength of response to overall inflation, $\rho_\pi^*$ | | |
| $\rho_\pi^* = 1.0001$ | –1.045 | –0.149 |
| $\rho_\pi^* = 1.5$ | –0.997 | –0.100 |
| $\rho_\pi^* = 2.5$ | –0.824 | 0.073 |
| $\rho_\pi^* = 3$ | –0.776 | 0.121 |
| $\rho_\pi^* = 5$ | –0.718 | 0.179 |
| $\rho_\pi^* = 10$ | –0.822 | 0.075 |
| Adjusted strength of response to the output gap, $\rho_x$ | | |
| $\rho_x = 0$ | –1.707 | –0.811 |
| $\rho_x = 0.1$ | –1.053 | –0.156 |
| $\rho_x = 0.2$ | –0.731 | 0.166 |
| $\rho_x = 0.5$ | –0.392 | 0.504 |
| $\rho_x = 1$ | –0.252 | 0.644 |
| $\rho_x = 10$ | –0.128 | 0.768 |

*Note*. The policy smoothing parameter ($\rho_r$) and the sectoral weights ($\rho_\pi^{**}(s)$, $s, = 1, \ldots, S$) remain fixed at their respective posterior modes.