4. An Estimation of Sectoral Price Stickiness Using Aggregate Data[1]

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Abstract

This article studies how to employ aggregate data to estimate sectoral price stickiness, which is described by the Calvo-style price setting. We find that sectoral price stickiness cannot be effectively estimated by the Bayesian approach of the multi-sector new Keynesian model that is used in Carvalho and Dam (2010). Then, we propose a structural GMM estimation of sectoral new Keynesian Phillips curves to obtain sectoral price stickiness and the results are well consistent with the available microeconomic evidence on price setting.

Keywords: sectoral price stickiness, sectoral new Keynesian Phillips curve, aggregate data, GMM, Bayesian approach

JEL Classification: E12, E31, C36

1. Introduction

Sticky-price dynamic stochastic general equilibrium (DSGE) models have become the main tools of monetary policy analysis[4]. These models often assume that goods are different enough to confer the producer a degree of monopoly power, but are otherwise identical. Although this approach simplifies aggregation, it also neglects much important sectoral heterogeneities, for example, sectoral heterogeneity in price stickiness. A few theoretical studies, such as Carvalho (2006), Bouakez *et al*. (2009), Nakamura and Steinsson (2010) and Eusepi *et al*. (2011) find that sectoral

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[4] *See, among many others, Yun (1996), Rotemberg and Woodford (1999), Bernanke et al. (1999), Chari et al. (2000), Erceg et al. (2000), and Christiano et al. (2005).*

heterogeneity in price stickiness has an important influence on the transmission and the effect of monetary policy. Thus, the estimation of sectoral price stickiness is essential to study monetary problems in a multi-sector framework.

Many studies use micro price data from various sources to estimate sectoral price stickiness and find that there is statistically significant and quantitatively important heterogeneity in price stickiness across sectors, such as Bils and Klenow (2004), Nakamura and Steinsson (2008), and Klenow and Kryvtsov (2008) for the United States, and the studies of Avarez *et al*. (2006), Dhyne *et al*. (2006), and Vermeulen *et al*. (2006) for the Euro area. However, in many countries there is limited availability of micro price data. Thus, the estimation of sectoral price stickiness using aggregate data is meaningful. If the macro-based estimates line up reasonably well with the microeconomic evidence when the latter is available, perhaps we can rely on them in the absence of that evidence. Even in the case that there is reliable micro-based estimation, macro-based estimation is also useful, because it is possible that some price adjustments do not convey information about changes in macroeconomic conditions, while others do. In that case, macro-based estimates should convey useful information about the price changes that do matter for aggregate dynamics, as Carvalho and Dam (2010) point out.

Using only aggregate data as observables, Carvalho and Dam (2010) employ a Bayesian approach to estimate multi-sector sticky-price models for twelve countries to obtain cross-sectional distribution of price stickiness. They find that inferred distributions of sectoral price stickiness conform quite well to empirical distributions constructed from the available microeconomic evidence on price setting. They assume the specification of staggered price setting inspired by Taylor (1979, 1980). Taylor (1979, 1980) assumes that only a fraction of prices is negotiated each period because of the presence of multiperiod nominal contracts. If firms set a price during a period, then the price will remain in place for a fixed number of periods. Obviously, Taylor (1979, 1980) is a deterministic model of price adjustment, because firms know when price can be reset and when it must remain unchanged.

This article studies how to employ aggregate data to estimate sectoral price stickiness described by the random model of price adjustment in Calvo (1983), because Calvo-style price setting can better describe price stickiness in the real economy than the Taylor-style price setting, as denoted by Kiley (2002), and then it is more widely used in the monetary model. We assume the economy consists of eight sectors which correspond to eight major groups defined by the BLS of the United States, and then estimate the price stickiness of these eight groups. Besides adopting different price setting, the difference between this article and Carvalho and Dam (2010) also reflects in that Carvalho and Dam (2010) assume the price stickiness of each sector is known and then estimate their weights in the economy; that is, the cross-sectional distribution of price stickiness, while we choose expenditure shares of eight major groups in the U.S. CPI as sectoral weights, and then estimate the price stickiness of each sector.

We firstly adopt the same approach as Carvalho and Dam (2010), which is employing a Bayesian approach of multi-sector sticky-price models to estimate sectoral price stickiness. However, our experiment shows that if the random model of price adjustment in Calvo (1983) is employed to describe sectoral price stickiness, the sectoral price stickiness cannot be effectively estimated. We think that, there are maybe two reasons for this problem. Firstly, the random model of price adjustment in Calvo (1983) is more complicated than the deterministic model of price adjustment in Taylor (1979, 1980), and then is more difficult to identify. Secondly, the Bayesian estimation of DSGE model requires that shocks are at least many as observables, and then does not allow you to identify all your parameters. Then, we propose a structural GMM estimation of sectoral new Keynesian Phillips curves to obtain sectoral price stickiness, and the results are well consistent with the available microeconomic evidence on price setting.

The remainder of the paper is organized as follows. Section 2 introduces the method of Carvalho and Dam (2010) and shows that this method cannot effectively estimate sectoral price stickiness described by the Calvo-style price setting, Section 3 proposes a method to estimate sectoral price stickiness by structural GMM estimation of sectoral new Keynesian Phillips curves, Section 4 uses this method to estimate price stickiness of eight major groups in the U.S. CPI, and Section 5 concludes the paper.

2. Bayesian Estimation of Sectoral Price Stickiness

In the semi-structural model of Carvalho and Dam (2010) there is a continuum of monopolistically competitive firms divided into K sectors that differ in the frequency of price changes. The distribution of firms across sectors is summarized by a vector $(\omega_1, \omega_2, \cdots, \omega_K)$, with $\omega_k > 0$ and $\sum_{k=1}^{K} \omega_k = 1$, where ω_k gives the mass of firms in sector k. They assume the specification of staggered price setting inspired by Taylor (1979, 1980). Firms set prices that remain in place for a fixed number of periods. The latter is sector-specific, and they save on notation by assuming that firms in sector k set prices for k periods. Thus, $(\omega_1, \omega_2, \cdots, \omega_K)$ fully characterizes the cross-sectional distribution of price stickiness. The semi-structural DSGE model used to estimate the cross-sectional distribution of price stickiness consists of three kinds of equations: the first order condition of sectoral pricing problem, an AR(1) process describing nominal output and an AR(1) process describing potential output. By Bayesian approach, they estimate $(\omega_1, \omega_2, \cdots, \omega_K)$ and find that inferred distributions of price stickiness conform quite well to the empirical distributions constructed from the available microeconomic evidence on price setting.

This article describes sectoral price stickiness by the random model of price adjustment in Calvo (1983), because Calvo-style price setting can better describe price stickiness in the real economy and is more widely used in the monetary model. Moreover, the partition of sectors can easily correspond to sectors of real economy when Calvo-style price setting is adopted, but the partition of sectors cannot correspond to sectors of real economy in Carvalho and Dam (2010). For example, we can divide the economy into several sectors according to CPI classification and this partition of sectors is meaningful both for micro agents and macro economy. Almost all countries have survey data of sectoral expenditure share and sectoral price index according to CPI classification. And then, we can analyze the transmission in different sectors of monetary policy, and the impact on aggregate economy of sectoral shocks and how to respond to them. Existing researches about multi-sector monetary policy, such as Bouakez *et al*. (2009), Nakamura and Steinsson (2010) and Eusepi *et al*. (2011) often adopt this method.

The setup describing sectoral price stickiness by Calvo-style price setting is as following. The economy consists of J sectors. Each sector consists of a continuum $(0,1)$ of monopolistically competitive firms. Following the formula proposed in Calvo (1983), suppose that the index of price stickiness in sector j is θ_j, $j = 1, 2, \cdots, J$. In sector j, each firm may reset its price in the next period only with the probability $1-\theta_j$. As all firms in sector j have the same production technology and the same demand function, they will choose the same optimal price when they reset their prices. Thus, in each period, a fraction $1-\theta_j$ of firms in sector j resets the prices, while a fraction θ_j keeps prices unchanged. Thus, θ_j ($j = 1, 2, \cdots, J$) can well describe sectoral price stickiness. The larger θ_j, the larger sectoral price stickiness.

To estimate sectoral price stickiness, which is denoted by θ_j ($j = 1, 2, \cdots, J$), we must build a multi-sector DSGE model. Here we employ the model in Hou and Gong (2012). The equilibrium conditions include[5]:

$$-\sigma\hat{c}_t + \sigma E_t\{\hat{c}_{t+1}\} = \hat{i}_t - E_t\{\pi_{t+1}\} \tag{1}$$

$$\varphi\hat{n}_t + (\hat{n}_{jt} - \hat{n}_t)/\zeta = -\sigma\hat{c}_t + \hat{w}_{jt}, j = 1, 2, \cdots, J \tag{2}$$

$$\hat{y}_{jt} = \hat{n}_{jt}, j = 1, 2, \cdots, J \tag{3}$$

$$\widehat{mc}_{jt} = \hat{w}_{jt}, j = 1, 2, \cdots, J \tag{4}$$

$$\pi_{jt} = \beta E_t\{\pi_{j,t+1}\} + \lambda_j \widehat{mc}_{jt} + \lambda_j \hat{p}_{jt} + u_{jt}, j = 1, 2, \cdots, J \tag{5}$$

$$\hat{y}_t = \sum_{j=1}^{J} \xi_j \hat{y}_{jt} \tag{6}$$

$$\hat{y}_{jt} = \hat{y}_t + \hat{p}_{jt} \tag{7}$$

$$\pi_t = \pi_{jt} + \hat{p}_{jt} - \hat{p}_{jt-1} \tag{8}$$

$$\hat{y}_t = \hat{c}_t + g_t \tag{9}$$

$$\hat{n}_t = \sum_{j=1}^{J} \xi_j \hat{n}_{jt} \tag{10}$$

$$\hat{i}_t = \rho^i \hat{i}_{t-1} + (1-\rho^i)(\phi_\pi \pi_t + \phi_y \hat{y}_t) + v_t \tag{11}$$

[5] *In following equations,* $\hat{x}_t$ *is log-deviation of a variable* X_t *from its steady state* X*, that is* $\hat{x}_t = \ln(X_t / X)$.

$$u_{jt} = \rho_j^u u_{j,t-1} + \varepsilon_{jt}^u,\ j = 1,2,\cdots,J \tag{12}$$

$$g_t = \rho^g g_{t-1} + \varepsilon_t^g \tag{13}$$

$$v_t = \rho^v v_{t-1} + \varepsilon_t^v \tag{14}$$

Equations (1) and (2), respectively, describe consumption decision and labor decision of the representative household, where $\hat{c}_t$ is household's consumption in period t, $\hat{i}_t$ is nominal interest rate, π_t is aggregate inflation, $\hat{n}_t$ is aggregate labor supply, $\hat{n}_{jt}$ is labor supply in sector j, $\hat{w}_{jt}$ is real wage in sector j, σ is the coefficient of relative risk aversion of household, $1/\varphi$ is the real wage elasticity of labor supply, ζ is the elasticity of substitution between sectoral labors. Equations (3), (4) and (5), respectively, describe sectoral production function, real marginal cost and inflation dynamics, where equation (5) is the sectoral new Keynesian Phillips curves, $\hat{y}_{jt}$ is sectoral output, $\widehat{mc}_{jt}$ is sectoral real marginal cost, π_{jt} is sectoral inflation, $\hat{p}_{jt}$ is sectoral price gap that is the log-difference between the aggregate price and the sectoral price, u_{jt} is a sectoral inflation shock in sector j, β is the discount factor and $\lambda_j = (1-\beta\theta_j)(1-\theta_j)/\theta_j$. Equations (6), (7) and (8) describe the relationship among aggregate output $\hat{y}_t$, aggregate inflation π_t, sectoral output, sectoral inflation and sectoral price gap, where $\xi_j \in (0,1)$ is the expenditure share of sector j and satisfies $\sum_{j=1}^{J} \xi_j = 1$. Equations (9) and (10) describe clearing condition of goods market and labor market, where g_t is a government purchases shock. Equation (11) is a Taylor rule with interest rate smoothing, where ρ^i is the coefficient of interest rate smoothing, ϕ_π and ϕ_y, respectively describe the strength of nominal interest rate responding to aggregate inflation and aggregate output gap, v_t is a monetary policy shock. Equations (12), (13) and (14) employ AR(1) process to describe sectoral inflation shocks, government purchases shock and monetary policy shock.

The model is estimated by the Bayesian approach using quarterly data available for the U.S. from 1993:Q1 to 2011:Q4. Assume the economy consists of eight sectors, which correspond to eight major groups of CPI and include *Food and beverages, Housing, Apparel, Transportation, Medical care, Recreation, Education and communication, Other goods and services*. The data series include the aggregate output gap, the nominal interest rate and the sectoral inflation. We use the difference between the real GDP and potential real GDP constructed by the Congressional Budget Office (CBO) to build the aggregate output gap, $\tilde{y}_t$. The quarterly interest rate is the quarterly average of the federal funds rate. The sectoral inflations are calculated according to the following formulas: $\pi_{jt} = \ln(P_{jt} / P_{j,t-1})$. All data are taken in deviation from the mean and seasonally adjusted.

Some of the parameters are calibrated based on judgment or previous estimations in the literature, because the multi-sector new Keynesian model is more complicated than the single-sector one, and its estimation requires more sample. The discount factor is $\beta = 0.96^{1/4}$, which is consistent with the annualized real interest rate of 4%. The subutility function over consumption is chosen to be logarithmic ($\sigma = 1$) and the Frisch elasticity of labor supply is set to unity ($\varphi = 1$). According to Horvath's (2000) estimation, the elasticity of substitution between labor sectors is set to unity ($\varsigma = 1$). Sectoral weights, ξ_j, are chosen as the expenditure shares of eight major groups in the U.S. CPI. The final set of parameters to be estimated is given below:

$$\{\theta_1, \theta_2, \cdots, \theta_8, \phi_y, \phi_\pi, \rho^i, \rho^g, \rho^v, \sigma^g, \sigma^v\}$$

where: σ^g and σ^v are standard deviation of shocks[6]. The prior distributions of parameters are set following basically the proposals from Smets and Wouters (2003, 2005, 2007). For saving space, only the prior distributions of sectoral price stickiness are given in Table 1.

The Bayesian estimation uses two Metropolis-Hastings chains, each one featuring 500,000 extractions. The posterior distributions of sectoral price stickiness are shown in Table1.

Table 1

Prior and Posterior Distributions of Sectoral Price Stickiness

Parameter	Sector	Prior distribution	Prior mean	Posterior mean	95% Confidence interval
θ_1	Food and beverages	Beta	0.8	0.8021	(0.6505, 0.9624)
θ_2	Housing	Beta	0.8	0.8006	(0.6501, 0.9607)
θ_3	Apparel	Beta	0.8	0.7985	(0.6458, 0.9600)
θ_4	Transportation	Beta	0.8	0.8023	(0.6498, 0.9591)
θ_5	Medical care	Beta	0.8	0.7993	(0.6450, 0.9557)
θ_6	Recreation	Beta	0.8	0.8021	(0.6530, 0.9594)
θ_7	Education and communication	Beta	0.8	0.8008	(0.6468, 0.9596)
θ_8	Other goods and services	Beta	0.8	0.7979	(0.6434, 0.9594)

[6] *We assume that there are only two exogenous shocks, namely the government purchases shock and the monetary policy shock. To check the robustness of Bayesian estimation, we add the sectoral inflation shock.*

Figures of posterior distribution, univariate convergence statistics and multivariate convergence statistics are presented in Appendices A, B and C. Both univariate and multivariate convergence statistics indicate that convergence was achieved, so we can believe the estimation led to meaningful results. However, our estimation of sectoral price stickiness does not show significant evidence of sectoral heterogeneity in price stickiness, which contradicts the existing micro-data evidence, such as Bils and Klenow (2004) and Nakamura and Steinsson (2008). They all conclude that there is statistically significant and quantitatively important heterogeneity in price stickiness across sectors. Thus, the contradiction maybe indicates that the Bayesian estimation of a multi-sector new Keynesian model cannot effectively estimate sectoral price stickiness if the random price adjustment in Calvo (1983) is employed to describe the sectoral price stickiness.

Why the same method can effectively estimate sectoral price stickiness described by the deterministic price adjustment in Taylor (1979, 1980), but it cannot if the random price adjustment in Calvo (1983) is employed? We think that there are maybe two reasons for this problem. Firstly, the Calvo-style price adjustment is more complicated than the Taylor-style price adjustment. Following Calvo (1983), each firm in sector j may reset its price in the next period only with the probability $1-\theta_j$, that is, firms have a random opportunity to reset price in every period. However, in the price adjustment model of Taylor (1979, 1980) firms either can or cannot reset price, which is deterministic. Obviously, sectoral heterogeneity in price stickiness described by the Calvo-style price adjustment is more complicated and more difficult to identify.

Moreover, the Bayesian estimation of the DSGE model requires that there are at least as many shocks as there are observables. It may be that this does not allow you to identify all your parameters: yielding posterior distributions are identical to prior distributions. The posterior distribution presented in appendix A shows that the yielding posterior distributions are indeed identical to the prior ones. In order to check the robustness of this result, we add sectoral inflation shocks into the model, and then the data of sectoral price gaps can be used in the Bayesian estimation. Sectoral price gaps are important variables determining sectoral inflation dynamics, as indicated by the sectoral new Keynesian Phillips curves. Thus, adding them into data series will increase the identification of sectoral heterogeneity in price stickiness. However, the results of estimation is worse and even convergence is not achieved because there are too many shocks (see Appendix D), which indicates further that the Calvo-style sectoral price stickiness cannot be effectively estimated by the Bayesian approach.

3. Method and Data of Structural GMM Estimation

In this section, we propose a structural GMM estimation of sectoral new Keynesian Phillips curves to obtain sectoral price stickiness using aggregate data. Before estimating, two important problems must be solved, which are how to express the sectoral inflation expectation $E_t\{\pi_{jt+1}\}$ and the sectoral real marginal cost $\widehat{mc}_{jt}$ in equation (5).

In Galí and Gertler (1999) and Galí *et al*. (2001, 2005), the agents are assumed having rational expectations about future inflation, and the error of inflation expectation is independent of lagged variables. Thus, in estimating the new Keynesian Phillips curves in a single-sector economy, the Generalized Method of Moments (GMM) can be used to estimate the coefficient of expected inflation using lagged variables as instrumental variables. Following this method, we assume the agents have rational expectations about future sectoral inflations, then the error of sectoral inflation expectation, $\pi_{j,t+1} - E_t\{\pi_{j,t+1}\}$, is not correlated with information before period t. The sectoral new Keynesian Phillips curves can be expressed as

$$\pi_{jt} = \beta\pi_{j,t+1} + \lambda_j \hat{mc}_{jt} + \lambda_j \hat{p}_{jt} + e_{jt} \tag{15}$$

where: $e_{jt} = -\beta(\pi_{j,t+1} - E_t\{\pi_{j,t+1}\})$.

The sectoral marginal cost is difficult to be expressed. There are two popular methods for measuring the marginal cost. The first uses the output gap, $\tilde{y}_t$, and the other employs the labor income share, ls_t (see Galí and Gertler, 1999; Galí *et al*., 2001, 2005; Linde, 2005; and Rudda and Whelan, 2005). However, even in a single-sector economy, the output gap $\tilde{y}_t$ and labor income share ls_t are different to the aggregate real marginal cost, $\hat{mc}_t$. Perhaps these differences are unimportant in the reduced-form estimation of the Phillips curve, but they are vital in the structural estimations and significantly affect the estimate of price stickiness index.

Firstly, we analyze the difference between the output gap and marginal cost in a single-sector economy. Assume that the utility function of the representative household is $U_t = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi}$, and the production function of firms is $Y_t = A_t N_t^{1-\alpha}$. Galí, Gertler and Lóez-Salido (2001) and Galí (2008) prove that if price stickiness is the only nominal friction, then $\hat{mc}_t = (\sigma + \frac{\varphi+\alpha}{1+\alpha})\tilde{y}_t$, that is, the marginal cost is proportional to the output gap. Furthermore, if there is also friction in labor market, then $\hat{mc}_t = (\sigma + \frac{\varphi+\alpha}{1+\alpha})\tilde{y}_t + \ln(\mu_t^w / \mu^w)$, where $\ln(\mu_t^w / \mu^w)$ is log-deviation of wage in period t, μ_t^w, from its steady state, μ^w. If firms have other variable inputs besides labor, such as capital and raw materials, then the relationship between the output gap and the marginal cost gap is more complicated. Thus, we assume that the marginal cost has the following random linear relationship with the output gap:

$$\hat{mc}_t = \phi\tilde{y}_t + v_t \tag{16}$$

where: v_t is measurement error. Then, the new Keynesian Phillips curve in single-sector economy can be expressed as

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \lambda\phi\tilde{y}_t + \lambda v_t \tag{17}$$

Secondly, we analyze the difference between the labor income share and marginal cost gap in a single-sector economy. Galí and Gertler (1999) indicate that the labor income share can correctly theoretically measure the marginal cost gap. However, as Galí, Gertler and Lóez-Salido (2001) and Galí (2008) point out, if the difference between the real marginal cost of a firm and the average real marginal cost in the economy is considered, then the new Keynesian Phillips curve in a single-sector economy is expressed as

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \lambda \Theta \widehat{mc}_t \tag{18}$$

where: ε is the elasticity of substitution between goods and $\Theta = \frac{1-\alpha}{1-\alpha+\alpha\varepsilon}$. Thus, even the labor income share can theoretically be an accurate measure of the marginal cost, there are notable differences between them if some realistic factors are considered, such as the difference between the real marginal cost of a firm and the average real marginal cost in the economy and the statistical error of the labor income share. So, we assume that the marginal cost has the following random linear relationship with the labor income share:

$$\widehat{mc}_t = \phi' lb_t + v_t' \tag{19}$$

where: v_t' is measurement error. Then, the new Keynesian Phillips curve in single-sector economy can be expressed as

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \lambda \phi' ls_t + v_t' \tag{20}$$

The above analysis shows that in the structural estimation of the new Keynesian Phillips curve in a single-sector economy the coefficient of output gap $\tilde{y}_t$ (or labor income share, ls_t) is not $\lambda \equiv (1-\beta\theta)(1-\theta)/\theta$, where θ is the aggregate price stickiness, but is the product of λ and some constant. Even in a single-sector economy, the correct structural form of ϕ or ϕ' cannot be obtained, because there are so many factors influencing them. Then, λ and θ cannot be deduced from the estimations of the coefficients of output gap $\tilde{y}_t$ or labor income share ls_t , that is, λ and θ are unidentifiable in a single-sector economy. In a multi-sector economy, this problem is more difficult to solve, because there is not data on sectoral output or sectoral labor income share. We adopt the following method to solve this problem.

Assume the sectoral marginal cost $\widehat{mc}_{jt}$ has the following random linear relationship with the aggregate output gap $\tilde{y}_t$:

$$\widehat{mc}_{jt} = \phi_j \tilde{y}_t + v_{jt} \tag{21}$$

where: v_{jt} is measurement error determined by sector-specific marginal cost shocks. Substituting equation (21) into equation (15) yields

$$\pi_{jt} = \beta \pi_{j,t+1} + \lambda_j \phi_j \tilde{y}_t + \lambda_j \hat{p}_{jt} + \eta_{jt} \tag{22}$$

where: $\eta_{jt} = e_{jt} + \lambda_j v_{jt}$.

From equation (22) we can discover an interesting phenomenon, that is, even the structure of ϕ_j is more complicated in the sectoral Phillips curves than the Phillips curve in a single-sector economy and the coefficients of λ_j and ϕ_j cannot be deduced from the estimations of the coefficients of the aggregate output gap $\tilde{y}_t$, the coefficient of sectoral price gap is λ_j . This feature can strengthen the identifying of λ_j and θ_j. Then, we can structurally estimate the sectoral Phillips curves to obtain θ_j by GMM and the orthogonal condition is

$$E\left\{[\theta_j \pi_{jt} - \beta\theta_j \pi_{t,t+1} - (1-\beta\theta_j)(1-\theta_j)\phi_j \tilde{y}_t - (1-\beta\theta_j)(1-\theta_j)\hat{p}_{jt}]\mathbf{z}_t\right\} = 0 \quad (23)$$

where: $\mathbf{z}_t$ is the set of instrumental variables. If the aggregate labor income share ls_t is used to describe the sectoral marginal cost $\hat{mc}_{jt}$, then the orthogonal condition is expressed as

$$E\left\{[\theta_j \pi_{jt} - \beta\theta_j \pi_{t,t+1} - (1-\beta\theta_j)(1-\theta_j)\phi_j' ls_t - (1-\beta\theta_j)(1-\theta_j)\hat{p}_{jt}]\mathbf{z}_t\right\} = 0 \quad (24)$$

To estimate this econometric equation, the sample data of sectoral inflation π_{jt}, sectoral price gap $\hat{p}_{jt}$ and aggregate output gap $\tilde{y}_t$ (or aggregate labor income share ls_t) are required.

We estimate the equation using quarterly data available for the U.S. from 1993:Q1 to 2011:Q4. We measure the sectoral inflations by the quarterly price indices for eight major groups defined by the BLS. CPI and the eight aforementioned price indices are fixed-base price indices and, hence, the sectoral price gap can be obtained by subtracting the sectoral price index from the CPI. We measure the sectoral price gaps according to the following formula: $\hat{p}_{jt} = \ln(P_t / P_{j,t-1})$. We use the difference between the real GDP and potential real GDP constructed by the Congressional Budget Office(CBO) to describe aggregate output gap $\tilde{y}_t$, and use labor income share of the non-farm business sector to measure the labor income share ls_t .

The set of instrumental variables include four lags of sectoral inflation, sectoral price gap, aggregate output, aggregate labor income share, aggregate inflation, the federal funds rate, M2 growth, the long-short interest rate spread, and commodity price inflation. Because the error of sectoral inflation expectation, e_{jt}, is not related to information before period t, and v_{jt} is determined by sector-specific marginal cost shock and then it is also not related to information before period t, the orthogonal condition is satisfied.

4. Results of Structural GMM Estimation

The consistency of GMM depends on whether the orthogonal condition holds. We adopt the Hansen J test to verify over-identifying restrictions of eight sectors and find that the null hypothesis “the orthogonal condition is satisfied” cannot be rejected (the results are given in Table 2). We also adopt the generalized F test of Stock and Yogo (2005) to verify whether there are weak instrumental variables about possible endogenous variables, $\pi_{j,t+1}$ and $\hat{p}_{jt}$. The results given in Table 2 show that all of the statistic of generalized F test are higher than ten, so there are no weak instrumental variables.

Table 2

Tests of Over-Identifying Restrictions and Weak Instrumental Variables

	Over-identifying restriction test		Generalized F test	
	J statistic	P value	$\pi_{j,t+1}$	$(\hat{p}_t - \hat{p}_{jt})$
Food and beverages	4.6632	1.0000	51.4977	139.625
Food at home	16.1063	0.9960	47.9699	149.874
Food away from home	6.5010	1.0000	88.4273	332.003
Housing	4.5923	1.0000	48.4635	33.6114
Shelter	4.7950	1.0000	24.8263	141.918
Fuels and utilities	4.7837	1.0000	130.612	147.815
Household furnishings and operations	6.7820	1.0000	139.843	260.777
Apparel	7.3113	1.0000	29.6412	126.304
Transportation	8.6069	1.0000	16.3191	283.882
Medical care	4.5914	1.0000	123.545	158.866
Recreation	12.4468	0.9997	49.6711	116.757
Education and communication	13.3818	0.9994	54.6403	376.904
Other goods and services	6.8513	1.0000	25.0958	287.837

The estimations of sectoral price stickiness for eight major groups defined by the BLS are given in Table 3, if the aggregate labor income share ls_t is used to describe sectoral marginal cost $\tilde{mc}_{jt}$. Our estimations show that at the flexible end are the transportation prices, almost 80 percent of which change quarterly; while at the sticky extreme are the medical care prices, with only 38 percent changing quarterly. When the group “Food and beverages” is divided into two categories: Food at home and Food away from home, we find that there are essential differences between the price sicknesses of these two categories. The price of Food at home is more flexible, and the price of Food away from home is stickier. When the group “Housing” is divided into three categories: Shelter, Fuels and utilities, Household furnishings and operations, the result is similar. The prices of Fuels and utilities are very flexible, almost 70 percent of which change quarterly. The prices of Shelter are very sticky, only 26 percent changing quarterly. Our estimations show that prices of services, such as Medical care, Food away from home and Shelter, are stickier than other groups, and the energy-related prices, such as Transportation and Fuels and utilities, are more flexible, that is consistent with the micro data evidence in Bils and Klenow (2004) and Nakamura and Steinsson (2008). When the aggregate output gap $\tilde{y}_t$ is used to describe the sectoral marginal cost $\widehat{mc}_{jt}$, the estimations are almost unchanged. Thus, our estimations are very robust.

In the last column of Table 3, the estimations of Bils and Klenow (2004) using micro-price data is given. Bils and Klenow (2004) provide monthly sectoral price stickiness for the following seven CPI major groups: Food and beverages, Household furnishings and operations, Apparel, Transportation, Medical care, Recreation, Other (including two categories: Education and communication, Other goods and services). The categories not covered are Shelter, Fuels and utilities. In Table 3, the monthly sectoral price stickiness in Bils and Klenow (2004) is translated into quarterly one by the following formula:

$$\theta_j^{quarter} = 1-(1-\theta_j^{month}) - \theta_j^{month}\cdot(1-\theta_j^{month}) - \theta_j^{month}\cdot\theta_j^{month}\cdot(1-\theta_j^{month}) \quad (25)$$

Table 3

The Estimation of Sectoral Price Stickiness

	Labor income share		Output gap		Bils and Klenow
	θ_j	95% Confidence interval	θ_j	95% Confidence interval	
Food and beverages	0.5521	(0.5268, 0.5774)	0.5425	(0.5165, 0.5684)	0.4168
Food at home	0.5019	(0.4475, 0.5564)	0.4900	(0.4507, 0.5293)	
Food away from home	0.7250	(0.6955, 0.7545)	0.7217	(0.6885, 0.7550)	
Housing	0.5813	(0.5614, 0.6012)	0.5800	(0.5624, 0.5977)	
Shelter	0.7408	(0.7214, 0.7603)	0.7411	(0.7239, 0.7583)	
Fuels and utilities	0.2981	(0.2772, 0.3191)	0.2988	(0.2840, 0.3136)	
Household furnishings and operations	0.5890	(0.5472, 0.6308)	0.5825	(0.5269, 0.6381)	0.3987
Apparel	0.4134	(0.3772, 0.4496)	0.4107	(0.3882, 0.4333)	0.3549
Transportation	0.1979	(0.1675, 0.2283)	0.1939	(0.1403, 0.2476)	0.2225
Medical care	0.6235	(0.6044, 0.6426)	0.6204	(0.6017, 0.6391)	0.7437
Recreation	0.4561	(0.4274, 0.4849)	0.4476	(0.4215, 0.4737)	0.6979
Education and communication	0.6040	(0.5660, 0.6420)	0.5948	(0.5784, 0.6112)	0.7050
Other goods and services	0.5035	(0.4659, 0.5411)	0.4985	(0.4601, 0.5369)	

The estimations in this article and Bils and Klenow ones (2004) have similar basic characters, although there are some differences in the numerical value of sectoral price stickiness. For example, the price of Transportation is most flexible and the price of Medical care is stickiest. The mean frequency of price adjustment is 1.56 quarters in our estimations, and the one is 1.67 quarters in Bils and Klenow (2004). Then, our estimations of sectoral price stickiness using macro-price data are well consistent with the one in Bils and Klenow (2004) using micro-price data.

5. Conclusion

Sectoral price stickiness is essential to study the monetary problems in a multi-sector framework and is often estimated by micro price data. As Carvalho and Dam (2010) denote, the estimation of sectoral price stickiness using aggregate data is also meaningful. This article studies how to employ aggregate data to estimate the sectoral price stickiness described by the Calvo-style price setting, because the Calvo-style price setting can better describe price stickiness in the real economy than the Taylor-style price setting and is more widely used in the monetary model.

We firstly adopt the same approach as Carvalho and Dam (2010); that is, employing a Bayesian approach of multi-sector sticky-price models to estimate sectoral price stickiness. However, our experiment shows that if the random model of price adjustment in Calvo (1983) is employed to describe sectoral price stickiness, the sectoral price stickiness cannot be effectively estimated. Then, we propose a structural GMM estimation of the sectoral new Keynesian Phillips curves to obtain the sectoral price stickiness. Our estimations show that the prices of services, such as Medical care, Food away from home and Shelter, are stickier than other groups, and the energy-related prices, such as Transportation and Fuels and utilities, are more flexible. The mean frequency of price adjustment is 1.56 quarters. These results are well consistent with the available microeconomic evidence on price setting.

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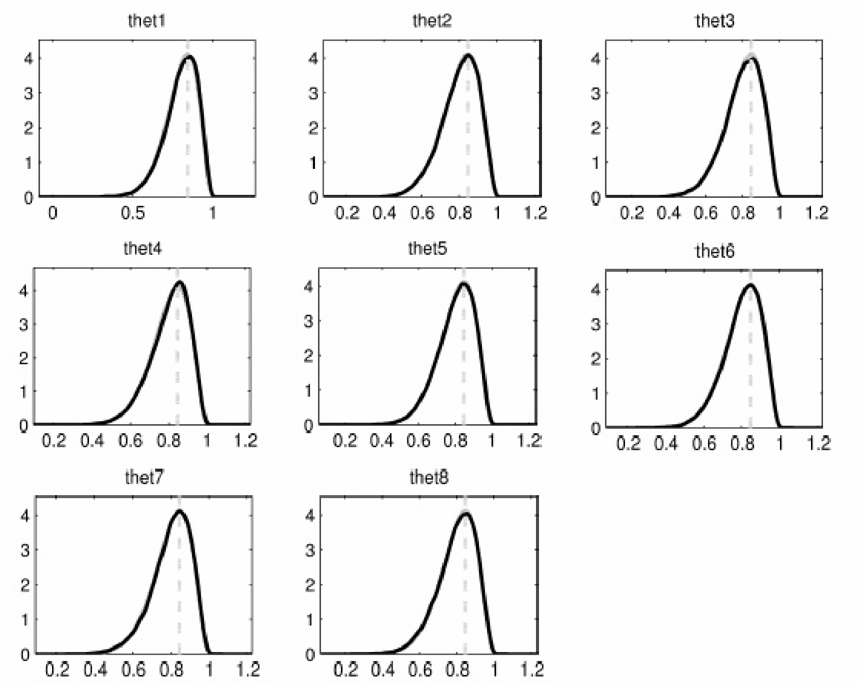
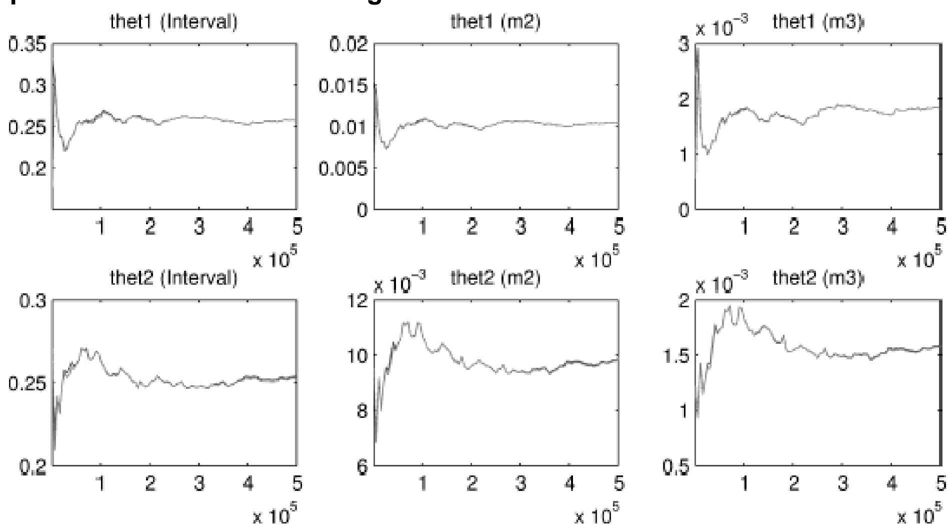
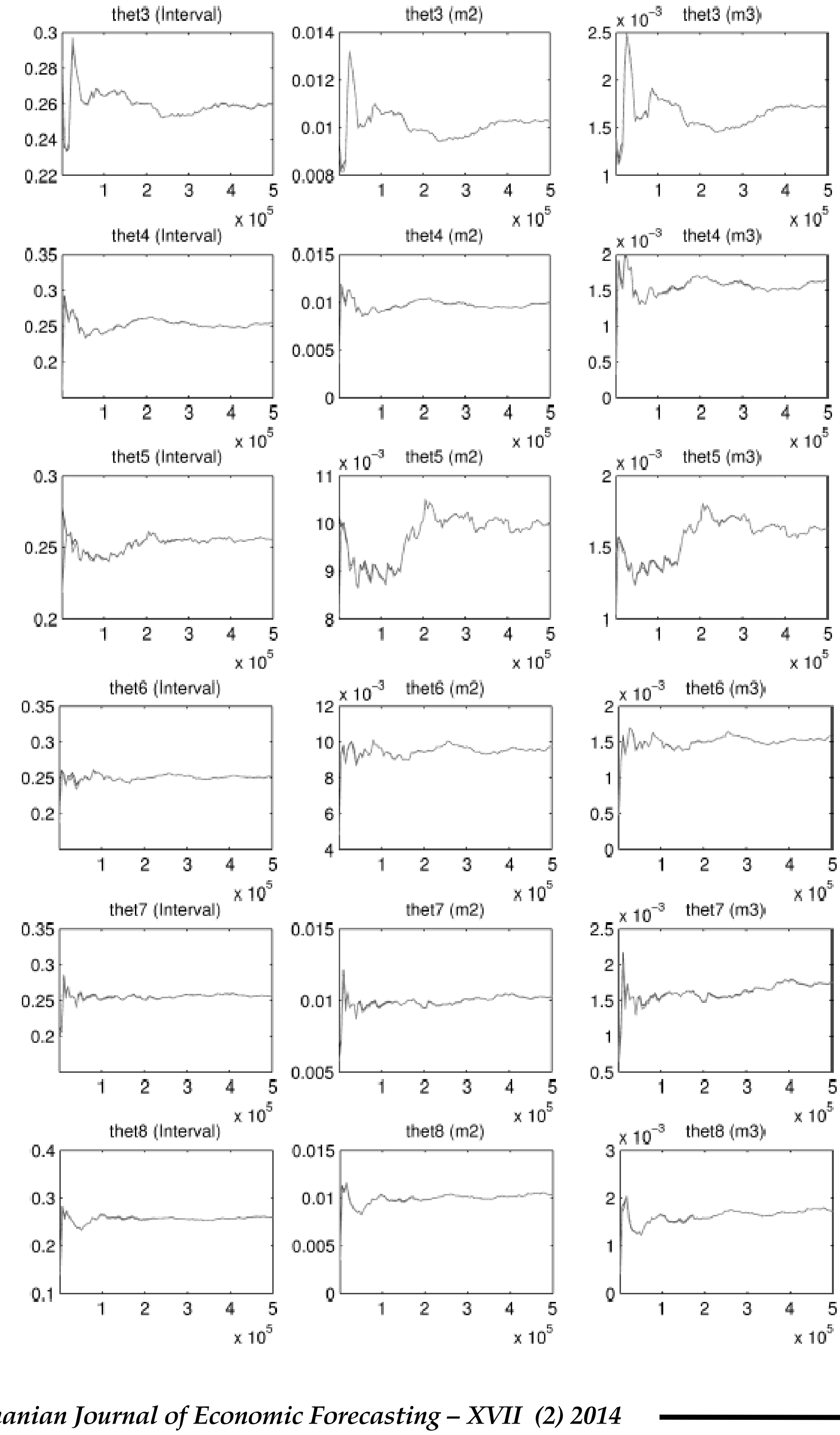
Appendices

Appendix A: Posterior Distribution of Sectoral Price Stickiness



Appendix B: Univariate Convergence Statistics

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thet3 (m2)
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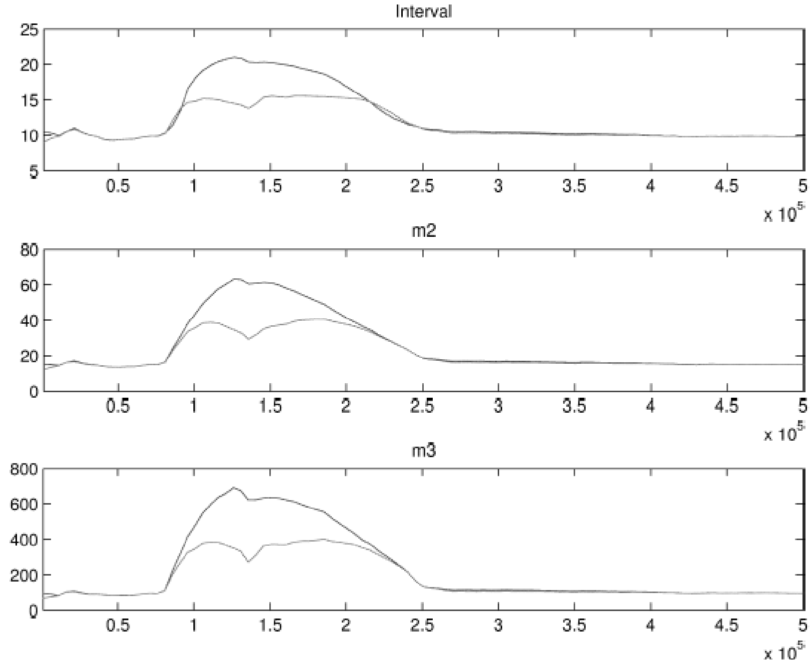
thet8 (m3)

Appendix C: Multivariate Convergence Statistics



Appendix D: Multivariate Convergence Statistics (with Sectoral Technology Shocks)