2005-16

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July 2005

Abstract

This paper constructs and estimates a sticky-price, Dynamic Stochastic General Equilibrium model with heterogenous production sectors. Sectors differ in price stickiness, capital-adjustment costs and production technology, and use output from each other as material and investment inputs following an Input-Output Matrix and Capital Flow Table that represent the U.S. economy. By relaxing the standard assumption of symmetry, this model allows different sectoral dynamics in response to monetary policy shocks. The model is estimated by Simulated Method of Moments using sectoral and aggregate U.S. time series. Results indicate 1) substantial heterogeneity in price stickiness across sectors, with quantitatively larger differences between services and goods than previously found in micro studies that focus on final goods alone, 2) a strong sensitivity to monetary policy shocks on the part of construction and durable manufacturing, and 3) similar quantitative predictions at the aggregate level by the multi-sector model and a standard model that assumes symmetry across sectors.

JEL Classification: E3, E4, E5
Key Words: Multi-sector models, sticky-price DGSE models, monetary policy

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1 Introduction

Economies involve the production and exchange of different goods produced in different sectors using distinct technologies and inputs. However, this heterogeneity is only partly acknowledged in standard sticky-price Dynamic Stochastic General Equilibrium (DSGE) models which have become the main tool of monetary policy analysis.[1] These models assume that goods are different enough to confer the producer a degree of monopoly power, but in the symmetric equilibrium all relative prices are equal to one and allocations are identical across sectors. This approach simplifies aggregation, but it also means that the standard model cannot address some important questions in monetary economics.

In addition to obvious realism, there are at least two reasons why sectoral heterogeneity matters. First, understanding sectoral responses to monetary policy shocks can be helpful in explaining the mechanism(s) through which money has real effects. For example, if nominal rigidity is concentrated in one or two sectors, then monetary policy can still have nontrivial effects on flexible-price sectors through input-output interactions. Second, sectoral heterogeneity has implications for the design of monetary policy. In contrast to the standard model where optimal monetary policy involves stabilizing the aggregate price level, research by Aoki (2001), Erceg and Levin (2002), Benigno (2004) and Huang and Liu (2004) shows that this strategy is sub-optimal in an economy where sectors are characterized by different degrees of nominal rigidity. Instead, these authors find potential welfare gains from targeting sectoral inflation rates.

This paper constructs and estimates a sticky-price DSGE model with heterogenous production sectors. Sectors are heterogenous in price stickiness, capital-adjustment costs, production functions, and the combination of goods used as material and investment inputs. In particular, sectors in this model use output from each other following an Input-Output Matrix and Capital Flow Table that represent the U.S. economy. The model is estimated by Simulated Method of Moments (SMM) using sectoral and aggregate U.S. time series. The main empirical results are the following. First, there is heterogeneity in price stickiness across sectors. This heterogeneity is large and statistically significant. The null hypothesis that prices are flexible can be rejected for services and durable manufacturing, but not for the other sectors. These results are in qualitative agreement with micro evidence for the U.S. (Bils and Klenow, 2004) and other countries. However, they also imply a quantitatively larger difference between the price rigidity of services and goods than previously

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[1]See, among many others, Blanchard and Kiyotaki (1987), Yun (1996), Rotemberg and Woodford (1997), Chari, Kehoe and McGrattan (2000), Kim (2000), Ireland (2001, 2003), and Christiano, Eichenbaum and Evans (2005).

reported. One reason is that estimates in this paper are based on both final and intermediate goods. Micro studies on intermediate goods (see Carlton, 1986) find long-term relations between buyer-seller pairs and larger price rigidity than for final goods. This is important because data from the Input-Output accounts indicate that services is the largest producer of intermediate goods in the U.S. economy.

Second, there is substantial heterogeneity in the response of sectoral variables to monetary policy shocks. In particular, output in construction, durable manufacturing, and services increase proportionally more than in the other sectors, but the mechanisms by which these responses take place are different. The response of services reflects the partial accommodation of a demand increase by the monopolistically competitive producer of a sticky-price good. The response of construction is due to the input-output structure of the economy and, in particular, to the increase in demand for investment goods by other sectors. The response of durable manufacturing is due to a combination of these two mechanisms. Although prices in agriculture, mining and nondurable manufacturing are flexible and these sectors do not produce capital goods, their output increases because they produce material inputs employed by the other sectors. In summary, the output effects of a monetary policy shock arise from price stickiness in some sectors of the economy and are transmitted to the other sectors via the input-output structure. The observation that output responses to monetary policy shocks are positively correlated across sectors and are larger on the part of durable-good producers is also documented by the Vector Autoregressions (VAR) in Barth and Ramey (2001), Dedola and Lippi (2003), and Peersman and Smets (2005). In general, however, VAR analysis does not reveal the economic mechanism by which the heterogenous sectoral responses arise.

Finally, in the presence of moderate frictions in the transfer of capital and labor across sectors, the aggregate predictions of the multi-sector and standard symmetric models are similar. Hence, modeling sectoral heterogeneity and interactions explicitly does not modify in a substantive manner the aggregate implications of DSGE models. This result is important because it suggests that previous literature that imposes symmetry across sectors may still provide a reasonable characterization of the dynamics of aggregate variables.

The paper is organized as follows. Section 2 constructs the monetary model with heterogeneous production sectors. Section 3 describes the data and econometric methodology, and reports the parameter estimates. Section 4 studies the properties of the estimated model. Finally, Section 4 discusses the limitations of this analysis and outlines future research.

2 A Monetary Economy with Heterogenous Production Sectors

2.1 Households

The economy is populated by identical, infinitely-lived households. The population size is constant and normalized to one. The representative household maximizes

$$E_\tau \sum_{t=\tau}^{\infty} \beta^{t-\tau} U\left(C_t, m_t, 1 - N_t\right), \tag{1}$$

where $\beta \in (0,1)$ is the subjective discount factor; $U(\cdot)$ is an instantaneous utility function that satisfies the Inada conditions and is assumed to be strictly increasing in all arguments, strictly concave, and twice continuously differentiable; C_t is consumption; $m_t = M_t/P_t$ is real money balances; M_t is the nominal money stock; P_t is an aggregate price index; and N_t is hours worked. Since the total time endowment is normalized to one, $1 - N_t$ represents leisure time.

Consumption is a constant-elasticity-of-substitution (CES) aggregate over the J available goods:

$$C_t = \left(\sum_{j=1}^{J} \xi^j (c_t^j)^{(\theta-1)/\theta}\right)^{\theta/(\theta-1)}, \tag{2}$$

where $\xi^j \in [0,1]$ are aggregation weights that satisfy $\sum_{j=1}^{J} \xi^j = 1$, c_t^j is the household's consumption of good j, and $\theta > 1$ is the elasticity of substitution between different goods. Notice that since ξ^j can be equal to zero for a given good j, not all goods are necessarily final in the sense that they are ultimately consumed by households. Instead some goods might be intermediate, meaning that they are used only in the production of other goods. The price index P_t is defined as

$$P_t = \left(\sum_{j=1}^{J} (\xi^j)^\theta (p_t^j)^{1-\theta}\right)^{1/(1-\theta)}, \tag{3}$$

where p_t^j is the price of good j. Because P_t is the price index associated with the bundle of goods consumed by households, it can be interpreted as the Consumer Price Index (CPI) in our model economy.

Households have a preference for diversity in their labor supply. That is,

$$N_t = \left(\sum_{j=1}^{J} (n_t^j)^{(\varsigma+1)/\varsigma}\right)^{\varsigma/(\varsigma+1)}, \tag{4}$$

[3]

where $\varsigma > 0$ and n_t^j is the number of hours worked in sector j at time t. This implies that households are willing to work a positive number of hours in every sector even if wages are not equal in all sectors. This assumption permits heterogeneity in wages and hours worked across sectors while preserving the representative-agent setup.[2]

In what follows, we specialize the instantaneous utility function to

$$U\left(C_t, m_t, 1 - N_t\right) = \log(C_t) + \eta_t \log(m_t) + \varrho \log(1 - N_t), \tag{5}$$

where $\varrho > 0$ is the utility weight of leisure and η_t is a strictly positive preference shock. The functional form of the instantaneous utility is motivated by theoretical results in Ngai and Pissarides (2004) who show that necessary and sufficient conditions for the existence of an aggregate balanced growth path in a multi-sector economy are logarithmic preferences and a non-unit price elasticity of demand.

There are $J + 2$ financial assets in this economy: money, a one-period interest-bearing nominal bond, and shares in each of the J productive sectors. The household enters period t with M_{t-1} units of currency, B_{t-1} nominal private bonds, and s_{t-1}^j shares in sectors $j = 1, \ldots, J$, and then receives interests and dividends, wages from its work in each sector, and a lump-sum transfer from the government. These resources are used to finance consumption and the acquisition of financial assets to be carried over to next period. Expressed in real terms, the household's budget constraint in every period is

$$b_t + \sum_{j=1}^{J} \frac{p_t^j c_t^j}{P_t} + \sum_{j=1}^{J} \frac{a_t^j s_t^j}{P_t} + m_t = \frac{R_{t-1} b_{t-1}}{\pi_t} + \sum_{j=1}^{J} \frac{w_t^j n_t^j}{P_t} + \sum_{j=1}^{J} \frac{(d_t^j + a_t^j) s_{t-1}^j}{P_t} + \frac{m_{t-1}}{\pi_t} + \frac{\Upsilon_t}{P_t}, \tag{6}$$

where $b_t = B_t / P_t$ is the real value of nominal bond holdings, a_t^j is the unit price of a share in sector j, d_t^j is the dividend paid by a share in sector j, R_t is the gross nominal interest rate on bonds that mature at time $t + 1$, π_t is the gross inflation rate between periods $t - 1$ and t, w_t^j is the nominal wage in sector j, and Υ_t is the government lump-sum transfer.

The household's utility maximization is carried out by choosing optimal sequences $\{c_t^j, n_t^j, M_t, B_t, s_t^j\}_{t=\tau}^{\infty}$ subject to the sequence of budget constraints (6), a no-Ponzi-game condition, and initial asset holdings $s_{\tau-1}^j$, $M_{\tau-1}$, and $B_{\tau-1}$. The $3J + 2$ first-order conditions for this problem determine the consumption demand for each good, labor supplied to each sector and money demand, and price the nominal bond and the shares in each sector. In particular,

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[2]The aggregator (4) implies that, strictly speaking, N_t is an index of hours worked. Only in the special case where $\varsigma \to \infty$ and the aggregator is linear does N_t correspond to total hours worked. However, in this case, hours worked in each sector are perfect substitutes and, consequently, the model would predict counterfactually that wages are the same in all sectors.

the consumption demand for each good is

$$c_t^j = (\xi^j)^\theta \left(\frac{p_t^j}{P_t}\right)^{-\theta} C_t, \tag{7}$$

where the price elasticity of demand is $-\theta$. Using this demand function and the definition of the price index, it is easy to show that $\sum_{j=1}^{J} p_t^j c_t^j = P_t C_t$.

2.2 Firms

The J differentiated goods are produced in monopolistically competitive sectors. The number of firms in each sector is normalized to one. As in Dixit and Stiglitz (1977), it is assumed that J is large enough that firms take aggregate variables as given and do not engage in strategic behavior. The representative firm in sector j uses the technology,

$$y_t^j = (k_t^j)^{\alpha^j} (z_t n_t^j)^{\nu^j} (H_t^j)^{\gamma^j}, \tag{8}$$

where y_t^j is output, k_t^j is capital, z_t is an aggregate labor-augmenting productivity shock, H_t^j is material inputs, and the parameters $\alpha^j, \nu^j, \gamma^j \in (0,1)$ and satisfy the linear restriction $\alpha^j + \nu^j + \gamma^j = 1$. The effect of a productivity shock will be different across sectors because sectors differ in factor intensities.[3]

Material inputs are goods produced by other sectors that are used as inputs in the production of good j. These inputs are combined according to

$$H_t^j = \left(\sum_{i=1}^{J} \zeta_{ij} (h_{i,t}^j)^{(\theta-1)/\theta}\right)^{\theta/(\theta-1)}, \tag{9}$$

where $h_{i,t}^j$ is the quantity of input i purchased by sector j and $\zeta_{ij} \in [0,1]$ is the weight that input i receives in sector j. The weights ζ_{ij} satisfy the condition $\sum_{i=1}^{J} \zeta_{ij} = 1$. The weights ζ_{ij} and quantities $h_{i,t}^j$ are indexed by j because every sector uses a different input combination in its production process. For the empirical analysis of the model, estimates of ζ_{ij} are constructed using the Use Table of the U.S. Input-Output accounts. The price of the composite good H_t^j is

$$Q_t^{H^j} = \left(\sum_{i=1}^{J} (\zeta_{ij})^\theta (p_t^i)^{1-\theta}\right)^{1/(1-\theta)}. \tag{10}$$

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[3]In an earlier version of this paper, productivity shocks were modeled as sector specific. However, their process parameters were poorly identified unless arbitrary restrictions were imposed during the estimation of the model. In addition, it is well known that the effect of uncorrelated sector-specific shocks tends to dissipate through aggregation due to the law of large numbers (see Dupor, 1999).

Firms own directly their capital stock. The stock of capital follows the law of motion

$$k_{t+1}^j = (1 - \delta^j)k_t^j + X_t^j, \tag{11}$$

where δ^j is the sector-specific rate of depreciation and X_t^j is an investment technology that aggregates different goods into additional units of capital. Specifically,

$$X_t^j = \left(\sum_{i=1}^{J} \kappa_{ij}(x_{i,t}^j)^{(\theta-1)/\theta} \right)^{\theta/(\theta-1)}, \tag{12}$$

where $x_{i,t}^j$ is the quantity of good i purchased by sector j for investment purposes and $\kappa_{ij} \in [0,1]$ is the weight that good i receives in the production of capital in sector j. The weights κ_{ij} satisfy the condition $\sum_{i=1}^{J} \kappa_{ij} = 1$. Empirical estimates of κ_{ij} are constructed below using data from the U.S. Capital Flow Table. The price of the composite investment good X_t^j is

$$Q_t^{X^j} = \left(\sum_{i=1}^{J} (\kappa_{ij})^\theta (p_t^i)^{1-\theta} \right)^{1/(1-\theta)}. \tag{13}$$

Adjusting the capital stock is assumed to involve a quadratic cost that is proportional to the current capital stock,

$$\Gamma_t^j = \Gamma(X_t^j, k_t^j) = \frac{\chi^j}{2} \left(\frac{X_t^j}{k_t^j} - \delta^j \right)^2 k_t^j, \tag{14}$$

where χ^j is a nonnegative parameter.

Equation (12) allows each sector to use different goods in different quantities to accumulate a stock of capital that is sector specific. Note, however, that the specificity of capital in this model is different from the one in Woodford (2005) and Altig, Christiano, Eichenbaum and Linde (2005). In those models, firms accumulate a form of capital that is not transferable to other firms. This real rigidity helps reconcile the quantitatively small estimate of the coefficient of the marginal cost in the New Keynesian Phillips curve with the high frequency of price adjustments found in micro data. In this model, capital is sector specific only in the sense that the nonlinear combination of investment inputs is different across sectors. However, the composite X_t^j can be unbundled and its parts sold to other sectors in a market with frictions of the form described by equation (14).

The assumption that the elasticity of substitution between goods is the same in equations (2), (9) and (12) implies that the price elasticity of demand of good i does not depend on the use given to the good by the buyer. Hence, the monopolistically competitive producer of good i will charge the same price to firms in all sectors and to households regardless of

[6]

whether i is employed as investment good, consumption good, or material input.[4] Prices are assumed to be sticky. In particular, firm j faces the following real per-unit cost when changing its nominal price

$$\Phi_t^j = \Phi(p_t^j, p_{t-1}^j) = \frac{\phi^j}{2} \left(\frac{p_t^j}{\pi_{ss} p_{t-1}^j} - 1 \right)^2, \tag{15}$$

where $\phi^j \geq 0$ and π_{ss} is the steady-state rate of inflation.

To summarize, this model allows production sectors to be heterogenous in 1) capital, labor, and material input intensities, 2) depreciation rates, 3) adjustment costs to the capital stock, 4) price rigidity, and 5) the combination of goods used as investment and material inputs. The first four points follow from the assumption that the parameters $\alpha^j, \nu^j, \gamma^j, \delta^j, \chi^j$, and ϕ^j are sector specific. The fifth point follows from the observation that the weights κ_{ij} and ζ_{ij} and the quantities $x_{i,t}^j$ and $h_{i,t}^j$ vary across sectors. Since the investment technology is different in each sector, the composition of the capital stock in each sector will be different as well.

The nominal profits of firm j, which will be transferred to shareholders in the form of dividends, are

$$\begin{aligned}
d_t^j = \ & p_t^j \left(c_t^j + \sum_{i=1}^{J} x_{j,t}^i + \sum_{i=1}^{J} h_{j,t}^i \right) - w_t^j n_t^j - \sum_{i=1}^{J} p_t^i x_{i,t}^j - \sum_{i=1}^{J} p_t^i h_{i,t}^j \\
& - \Gamma_t Q_t^{X^j} - \Phi_t^j p_t^j \left(c_t^j + \sum_{i=1}^{J} x_{j,t}^i + \sum_{i=1}^{J} h_{j,t}^i \right),
\end{aligned} \tag{16}$$

where d_t^j is nominal profits and the terms in the right-hand side are, respectively, revenue from sales to households and firms, the wage bill, total expenditure on investment goods, total expenditure on material inputs, the cost of adjusting the capital stock and the cost of changing prices. The firm's problem is to maximize

$$E_\tau \sum_{t=\tau}^{\infty} \beta^{t-\tau} \left(\frac{\Lambda_\tau}{\Lambda_t} \right) \left(\frac{d_t^j}{P_t} \right), \tag{17}$$

by selecting optimal sequences $\{n_t^j, x_{it}^j, h_{it}^j, k_{t+1}^j, p_t^j\}_{t=\tau}^{\infty}$ subject to the production function (8), the law of motion for capital (11), total demand for good j, $y_t^j = c_t^j + \sum_{i=1}^{J} x_{j,t}^i + \sum_{i=1}^{J} h_{j,t}^i$, the condition that demand equals supply, and the initial capital stock and prices. The variable Λ_t in (17) is the household's marginal utility of wealth at time t. The kernel $\beta^{t-\tau} \Lambda_\tau / \Lambda_t$

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[4]It is easy to extend the model to allow different prices for firms and households, but this generalization requires the assumption of frictions that rule out arbitrage. We considered this strategy in the previous version of this paper, but found difficult to identify separately the price elasticities of demand of firms and households with our data set.

is used to value profits because the firm is owned directly by households through the stock market.

In order to solve this problem, we first conjectured the form of the demands $x_{j,t}^i$ and $h_{j,t}^i$. Given the functional forms employed here, natural candidates are $x_{j,t}^i = (\kappa_{ji})^\theta \left(p_t^j / Q_t^{X^i} \right)^{-\theta} X_t^i$ and $h_{j,t}^i = (\zeta_{ji})^\theta \left(p_t^j / Q_t^{H^i} \right)^{-\theta} H_t^i$. Then we showed that in equilibrium these are indeed the optimal demands of good j on the part of firms in the other sectors. For these demand functions, the relations $\sum_{i=1}^{J} p_t^i x_{i,t}^j = Q_t^{X^j} X_t^j$ and $\sum_{i=1}^{J} p_t^i h_{i,t}^j = Q_t^{H^j} H_t^j$ hold.

2.3 Monetary and Fiscal Policy

The government comprises both fiscal and monetary authorities. Fiscal policy consists of lump-sum transfers to households each period that are financed by printing additional money in each period. Thus, the government budget constraint is

$$\Upsilon_t / P_t = m_t - m_{t-1}/\pi_t, \tag{18}$$

where the term in the right-hand side is seigniorage revenue at time t. Money is supplied by the government according to $M_t = \mu_t M_{t-1}$, where μ_t is the stochastic gross rate of money growth.[5] In real terms, this process implies $m_t \pi_t = \mu_t m_{t-1}$.

2.4 Shocks

The exogenous shocks to the model, namely the preference shock η_t, the technology shock z_t, and the monetary policy shock μ_t, follow the processes

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\begin{aligned}
\ln(\eta_t) &= (1 - \rho_\eta) \ln(\eta_{ss}) + \rho_\eta \ln(\eta_{t-1}) + \epsilon_{\eta,t}, \\
\ln(z_t) &= (1 - \rho_z) \ln(z_{ss}) + \rho_z \ln(z_{t-1}) + \epsilon_{z,t}, \\
\ln(\mu_t) &= (1 - \rho_\mu) \ln(\mu_{ss}) + \rho_\mu \ln(\mu_{t-1}) + \epsilon_{\mu,t},
\end{aligned}
$$

where ρ_η, ρ_z, and ρ_μ are strictly bounded between -1 and 1; $\ln(\eta_{ss})$, $\ln(z_{ss})$ and $\ln(\mu_{ss})$ are the unconditional means of their respective shocks; and the innovations $\epsilon_{\eta,t}$, $\epsilon_{z,t}$ and $\epsilon_{\mu,t}$ are mutually independent, serially uncorrelated and normally distributed with mean zero and variances σ_z^2, σ_μ^2 and σ_b^2, respectively.

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[5]In preliminary work, we considered the case where monetary policy takes the form of a Taylor rule for the nominal interest rate. Calibration results were very similar to the ones reported below and are available from the corresponding author upon request. However, a potential problem with the econometric estimation of that version of the model is that the coefficients of the Taylor rule for the U.S. do not appear to be stable over the sample (see, Clarida, Gali and Gertler, 2000).

2.5 Aggregation and Equilibrium

In equilibrium, 1) private bond holdings equal zero because households are identical, and 2) the total share holdings in sector j add up to one. Thus, the aggregate counterpart of the representative household's budget constraint is

$$\sum_{j=1}^{J} \frac{p_t^j c_t^j}{P_t} + m_t = \sum_{j=1}^{J} \frac{w_t^j n_t^j}{P_t} + \sum_{j=1}^{J} \frac{d_t^j}{P_t} + \frac{m_{t-1}}{\pi_t} + \frac{\Upsilon_t}{P_t}. \tag{19}$$

Substituting the government budget constraint (18) into this equation and multiplying through by the price level yield

$$\sum_{j=1}^{J} p_t^j c_t^j = \sum_{j=1}^{J} w_t^j n_t^j + \sum_{j=1}^{J} d_t^j. \tag{20}$$

Let $V_t^j \equiv p_t^j \left(c_t^j + \sum_{i=1}^{J} x_{j,t}^i + \sum_{i=1}^{J} h_{j,t}^i \right)$ denote the value of gross output produced by sector j. Then, aggregate nominal dividends are equal to

$$\sum_{j=1}^{J} d_t^j = \sum_{j=1}^{J} V_t^j - \sum_{j=1}^{J} w_t^j n_t^j - \sum_{j=1}^{J} Q_t^{Xj} X_t^j - \sum_{j=1}^{J} Q_t^{Hj} H_t^j - \sum_{j=1}^{J} A_t^j, \tag{21}$$

where we have used $\sum_{i=1}^{J} p_t^i x_{i,t}^j = Q_t^{Xj} X_t^j$ and $\sum_{i=1}^{J} p_t^i h_{i,t}^j = Q_t^{Hj} H_t^j$, and defined $A_t^j = \Gamma_t^j Q_t^{Xj} + \Phi_t^j p_t^j \left(c_t^j + \sum_{i=1}^{J} x_{j,t}^i + \sum_{i=1}^{J} h_{j,t}^i \right)$ to be the sum of all adjustment costs in sector j. The nominal value added in sector j is denoted by Y_t^j, and it is defined as the value of gross output produced by that sector minus the cost of material inputs. That is,

$$Y_t^j = V_t^j - Q_t^{Hj} H_t^j. \tag{22}$$

Substituting (21) and (22) into (20), using $\sum_{j=1}^{J} p_t^j c_t^j = P_t C_t$, and rearranging yield

$$\sum_{j=1}^{J} Y_t^j = P_t C_t + \sum_{j=1}^{J} Q_t^{Xj} X_t^j + \sum_{j=1}^{J} A_t^j. \tag{23}$$

Thus, total output equals household consumption plus investment by all sectors plus the sum of all adjustment costs in all sectors.

The equilibrium of the model is not symmetric due to the heterogeneity in production. That is, relative prices are not all equal to one as is the case in the standard sticky-price model, and real wages and allocations are different across sectors. This observation has two implications for the solution of the model and the computation of its steady state. First,

the state variables of the system include J capital stocks and J real prices. Second, finding the steady-state allocations requires the solution of a set of $2J^2 + J$ nonlinear equations that determine labor, material and investment inputs in each sector. Then, the remaining allocations and all relative prices in steady state can be recovered from the model equations. In contrast, in the standard sticky-price model, the state vector includes only one capital stock and one real price, and all steady-state allocations are pinned down by the proportion of hours worked.

The model is solved numerically by log-linearizing the first-order and equilibrium conditions around the deterministic steady state to obtain a system of linear difference equations with expectations. The rational-expectation solution of this system is found using the approach in Blanchard and Kahn (1980).

3 Econometric Estimation

3.1 Data

The empirical analysis of the model is based on sectoral and aggregate U.S. time series at the quarterly frequency for the period 1959:1 to 2002:4. After the first half of 2003, the Bureau of Labor Statistics (BLS) stopped reporting sectoral data under the Standard Industry Classification (SIC) codes and switched to the new North American Industry Classification System (NAICS). This means that pre- and post-2003 sectoral data might not be fully comparable.

Although the theoretical model allows any level of disaggregation, this paper focuses on six broad sectors of the U.S. economy at the division level of the SIC, namely agriculture, mining, construction, durable manufacturing, nondurable manufacturing and services. The list of six sectors is exhaustive in the sense that their output aggregate to privately-produced U.S. Gross Domestic Product (GDP). Agriculture (Division A) includes the production of crops and livestock, agriculture-related services, and forestry. Mining (Division B) includes oil and gas extraction, metallic and nonmetallic mining, and mining-related services. Construction (Division C) includes building construction (for example, housing), heavy construction (for example, bridges) and special trade contractors (plumbing, electrical work, etc.). Although mining and construction respectively represent only 2.5 and 5.2 per cent of privately-produced GDP, their contribution to aggregate fluctuations may be large because they produce most of the energy goods[6] and fixed capital that enter the production function

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[6]Oil and gas production accounts for 73 per cent of the output value in the mining sector. These figure and the ones in the text are the averages of annual observations for the period 1959 to 2001.

of all sectors. The division of manufacturing between durables (Division D, Groups 24, 25, and 32 to 39) and nondurables (Division D, Groups 20 to 23 and 26 to 31) is based on the BLS definition of good durability. Finally, services (Divisions E to I) include, among others, wholesale and retail trade, transportation, communications, finance and health. As in the National Income and Product Accounts, rental housing is treated as a service for the purpose of computing the households' expenditure shares.

The number and size of the sectors is to some extent determined by data availability and computational considerations. SIC sectoral data are available at discrete aggregation levels, say division level (roughly six sectors), two-digit level (roughly thirty sectors), etc. In addition, BLS data tend to be much more exhaustive for manufacturing than for services. In particular, manufacturing categories are more finely divided than service ones. This means that the sector sizes are uneven and that service variables receive a large weight in the aggregates. On the other hand, focusing on the six sectors above has four advantages. First, these sectors are natural partitions of the U.S. economy. Second, they are associated with concrete goods, as opposed to the generic distinction between "sticky-price" and "flexible-price" goods in some two-sector models (see, for example, Ohanian et al., 1995). Third, they are computationally manageable. The computation of the steady state requires the solution of $2J^2 + J$ nonlinear equations, that is 78 equations for the six-sector model at division level but 1830 equations for the thirty-sector model at the two-digit level of the SIC. Finally, there are sufficient sectoral data to identify econometrically their sector-specific parameters.[7]

The sectoral data consist of quarterly series on Producer Price Indices at the division level of the SIC, observations on yearly expenditures on labor, capital and material inputs by each sector, and data from the U.S. Input-Output accounts. The commodity-based Producer Price Indices collected by the BLS for farm products, durable manufactured goods, and nondurable manufactured goods were used to construct sectoral inflation series for agriculture, durable manufacturing, and nondurable manufacturing, respectively.[8] Since the raw data are seasonally unadjusted, we control for seasonal effects by regressing each series on seasonal dummies and purging the seasonal components.

The data on input expenditures by each sector are used to construct estimates of the production function parameters (see Section 3.2 below). This data set was originally con-

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[7]A drawback of this level of disaggregation is that the assumption in the theoretical model that J is large enough such that firms take aggregate quantities as given is less plausible in this case. This means that, for example, the service sector may recognize its nonnegligible effect on the aggregate price level and behave strategically. These effects may be theoretically interesting, but we abstract from them in the empirical analysis that follows.

[8]The BLS only started constructing PPIs at the industry level in the mid-1980s. The three commodity-based indices mentioned above match well with their respective industries, but we were unable to find or construct similar matches for mining, construction, and services for the complete sample period.

structed by Dale Jorgenson and is described in detail in Jorgenson and Stiroh (2000). The observations are available at the annual frequency for the years 1958 to 1996 for more than 30 sectors, but aggregation up to the division level of the SIC is straightforward.

Data from the U.S. Input-Output (I-O) accounts are used to construct estimates of the weights ζ_{ij} and κ_{ij}. Input–Output accounts show how industries use output from and provide input to each other to produce gross domestic product. The Bureau of Economic Analysis (BEA) prepares both benchmark and annual I-O accounts. Benchmark accounts are produced every five years using detailed data from the economic censuses conducted by the Bureau of the Census. Annual accounts are prepared for selected years between the benchmarks using less comprehensive data than those from the censuses. We use the 1992 benchmark accounts because both the Use Table and the Capital Flow Table are electronically available for that year.[9]

The Use Table is used to construct the weights ζ_{ij}. Use Tables contain the value in producer prices of each input used by each U.S. industry. As in Horvath (2000), the weight ζ_{ij} is computed as the share of total input expenditures by sector j that goes into inputs from sector i.[10] The Capital Flow Table (CFT) is used to construct the weights κ_{ij}. The CFT shows the purchases of new structures, equipment and software, allocated by using industry in producer prices. The weight κ_{ij} is computed as the share of total investment expenditures by sector j that goes into inputs from sector i. Most of the investment commodities are produced by the construction and durable manufacturing sectors. The service sector has nonnegligible weights because it produces goods that are ancillary to investment, for example, engineering and landscaping services. Mining produces most of its own capital stock because exploration, shafts and wells in the oil industry are coded as goods produced in the mining sector in the I-O accounts. By construction, $\zeta_{ij}, \kappa_{ij} \in [0, 1]$ and $\sum_{i=1}^{J} \zeta_{ij} = \sum_{i=1}^{J} \kappa_{ij} = 1$ for all j.

The aggregate data consist of quarterly series on the rates of inflation, nominal money growth and nominal interest, and per capita real money balances, investment and consump-

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[9]The only other year for which this is true is 1982, but documentation is more extensive and user friendly for 1992 than for 1982.

[10]We equate commodities with sectors as in the theoretical model where good j is produced exclusively by sector j. This means that we are implicitly treating the Make Table of the I-O accounts as diagonal and it is the reason we can construct the weights ζ_{ij} using the Use Table alone. The Make Table contains the value of each commodity produced by each domestic industry and, in reality, it is not perfectly diagonal because there is a small proportion of commodities that are produced by industries in a different SIC division. For example, the I-O accounts treat printed advertisement as a business service (Division I) even though it is produced by the printing and publishing sector (Division D). In order to examine the quantitative importance of the off-diagonal terms, we computed the share of each commodity that is produced in each sector. Since the diagonal elements vary between 0.988 and 1, the original assumption of the model that associates each commodity with only one sector seems to the a reasonable approximation for the U.S. economy at this level of disaggregation.

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tion. With the exceptions noted below, the raw data were taken from the database of the Federal Reserve Bank of St-Louis. The inflation rate is the percentage change in the CPI. The rate of nominal money growth is the percentage change in M2. The nominal interest rate is the three-month Treasury Bill rate. Real money balances are computed as the ratio of M2 per capita to the CPI. Real investment and consumption are measured, respectively, by Gross Private Domestic Investment and Personal Consumption Expenditures per capita divided by the CPI. The raw investment and consumption series were taken from the National Income and Product Accounts produced by the BEA. Real balances, investment and consumption are computed in per capita terms in order to make these data compatible with the model, where there is no population growth. The population series corresponds to the quarterly average of the mid-month U.S. population estimated by the BEA. Except for the nominal interest rate, all data are seasonally adjusted at the source.

Since the variables in the model are expressed in percentage deviations from the steady state, all series were logged and quadratically detrended, except the rates of inflation (sectoral and aggregate), money growth, and nominal interest, which were logged and demeaned.

3.2   Methodology and Parameter Estimates

The model is estimated by Simulated Method of Moments (SMM). SMM has been proposed by McFadden (1989) and Pakes and Pollard (1989) to estimate discrete-choice problems, and by Lee and Ingram (1991) and Duffie and Singleton (1993) to estimate time-series models. SMM is attractive for the estimation of DSGE models for two reasons. First, the stochastic singularity of DGSE models imposes weaker restrictions on moments-based procedures than on Maximum Likelihood (ML). In particular, estimation requires the use of linearly independent moments for SMM, but linearly independent variables for ML. The former is a weaker restriction because it is possible to find independent moments that incorporate information about more variables than those that are linearly independent. Second, moments-based procedures are more robust to misspecification than ML. See Ruge-Murcia (2003) for further discussion.

In order to develop the reader's intuition, consider the following comparison between SMM and calibration. In calibration, the macroeconomist computes the unconditional moments of artificial series generated by the DSGE model given the parameter values, and then compares these artificial moments with the ones estimated using actual data. This comparison may be casual or based on measures of fit like the ones proposed, for example, by Gregory and Smith (1991) and Watson (1993). The Simulated Method of Moments also compares simulated and empirical unconditional moments, but then updates the estimates of

[13]

the parameter values in a manner that minimizes a well-defined measure of distance between the moments.

Formally, define $\mathbf{g}_t$ to be the vector of empirical observations on variables whose moments are of interest. Define $\mathbf{g}_\iota(\varphi)$ to be the synthetic counterpart of $\mathbf{g}_t$ whose elements are computed on the basis of artificial data generated by the model using parameter values φ. The sample size is denoted by T and the number of observations in the artificial time series is λT. The (optimal) SMM estimator, $\widehat{\varphi}$, is the value of φ that solves

$$\min_{\{\varphi\}} \mathbf{G}(\varphi)' \mathbf{W} \mathbf{G}(\varphi), \tag{24}$$

where

$$\mathbf{G}(\varphi) = (1/T) \sum_{t=1}^{T} \mathbf{g}_t - (1/\lambda T) \sum_{\iota=1}^{\lambda T} \mathbf{g}_\iota(\varphi),$$

and $\mathbf{W}$ is the optimal weighting matrix

$$\mathbf{W} = \lim_{T \to \infty} Var \left((1/\sqrt{T}) \sum_{t=1}^{T} \mathbf{g}_t \right)^{-1}. \tag{25}$$

Under the regularity conditions in Duffie and Singleton (1993),

$$\sqrt{T}(\widehat{\varphi} - \varphi) \to N(\mathbf{0}, (1 + 1/\lambda)(\mathbf{D}' \mathbf{W}^{-1} \mathbf{D})^{-1}), \tag{26}$$

where $\mathbf{D} = E(\partial \mathbf{g}_\iota(\varphi)/\partial \varphi)$ is a matrix assumed to be finite and of full rank.

The optimal weighting matrix, $\mathbf{W}$, is computed using the Newey-West estimator with a Barlett kernel, and the derivatives $\partial \mathbf{g}_\iota(\varphi)/\partial \varphi$ are computed numerically with the expectation approximated by the sample average of the simulated λT data points. The results reported below are based on $\lambda = 5$, meaning that the simulated series are 5 times larger than the sample size. The term $(1 + 1/\lambda)$ in (26) is a measure of the increase in sample uncertainty due to the use of simulation to compute the population moments. Using a larger value of λ permits a more accurate estimation of the simulated moments and increases the statistical efficiency of SMM, but it also increases the time required for each iteration of the minimization routine. Sensitivity analysis indicates that results are robust to the value of λ used.

In order to limit the effect of the starting values used to generate the artificial series, 100 extra observations were generated in every iteration of the minimization routine and the initial 100 observations were discarded. The seed in the random numbers generator is fixed throughout the estimation. The use of common random draws is essential here to calculate the numerical derivatives of the minimization algorithm. Otherwise, the objective function would be discontinuous and the optimization algorithm would be unable to distinguish a

[14]

change in the objective function due to a change in the parameters from a change in the random draw used to simulate the series.

A number of parameters were estimated or calibrated prior to SMM estimation. The reason is that the estimation of this model requires the computation of the steady state and the Blanchard-Khan solution of the model in every iteration of the optimization algorithm. The former is extremely costly computationally because it involves the solution of a large system of nonlinear equations. Thus, for estimation purposes, it is useful to distinguish between 1) parameters that affect the dynamics of the system but not the steady state, and 2) parameters that determine the steady state and may or may not affect the dynamics. The latter parameters include the subjective discount rate (β), the preference parameter ς, the parameters of the sectoral production functions $(\alpha^j, \nu^j, \text{ and } \gamma^j)$, the parameter θ that measures the elasticity of substitution in production and consumption, the sectoral depreciation rates (δ^j), and the consumption weights (ξ^j). An advantage of estimating these parameters beforehand is that solving (24) then requires only the computation of the model solution, but not of the steady state, in every iteration of the minimization routine.

The consumption weights, sectoral depreciation rates, and ς were taken from Horvath (2000). Horvath measures the consumption weights as the average expenditure shares in the National Income and Product Accounts from 1959 to 1995. The shares for agriculture, mining, construction, durable manufacturing, nondurable manufacturing and services are 0.02, 0.04, 0.01, 0.16, 0.29 and 0.48, respectively. The sectoral depreciation rates are 0.01, 0.02, 0.04, 0.02, 0.02 and 0.02, respectively. Finally, Horvath constructs an estimate of ς from a regression of the change in the relative labor supply on the change in the relative labor share in each sector. Since his results indicate that $\widehat{\varsigma} = 0.9996$ (0.0027), where the term in parenthesis is the standard error, we set $\varsigma = 1$ in our empirical analysis.[11]

An estimate of the subjective discount rate β was constructed using the sample average of the inverse of the gross *ex-post* real interest rate to obtain $\widehat{\beta} = 0.997$ (0.0005). By the Central Limit Theorem, this estimator is normally distributed with mean β and variance σ^2/T where $T = 175$ is the sample size and σ^2 is the variance of the π_{t+1}/R_t. Previous multi-sector models calibrate θ to values between 1 (Hornstein and Praschnik, 1997) and 3 (Bergin and Feenstra, 2000). We use $\theta = 2$, but results appear robust to using values similar to those employed in earlier multi-sector literature.[12] The mean of the technology shock is

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[11]In addition, we tested this parametric restriction using a Lagrange Multiplier (LM) test. Since the p-value is 0.70, the restriction is not rejected by our data at standard significance levels.

[12]The restriction $\theta = 2$ was tested using a LM test. The p-value was 0.35 meaning that this restriction would not be rejected by the data at standard levels. In preliminary calibrations, we considered larger values of θ, which would be consistent with earlier markup estimates in Basu and Fernald (1994). However, in this case, the model predicts counterfactually that mostly the good with the lowest relative price will be

calibrated to minimize the distance between the actual and predicted share of each sector in aggregate output. Due to the normalization that the total time endowment is equal to 1, the mean of this shock is just a scaling factor.

Estimates of the parameters of the production functions are constructed using data on annual labor, capital, and material inputs expenditures for each sector collected by Dale Jorgenson for the period 1958 to 1996. The real expenditures predicted by the model may be obtained from the first-order conditions of the firm's problem,[13]

$$\nu^j \left(\psi_t^j y_t^j \right) = \frac{w_t^j n_t^j}{P_t},\tag{27}$$

$$\gamma^j \left(\psi_t^j y_t^j \right) = \frac{\sum\limits_{i=1}^{J} p_t^i h_{i,t}^j}{P_t},\tag{28}$$

$$\alpha^j \left(\psi_t^j y_t^j \right) = \left(\left(\frac{\Lambda_{t-1}}{\beta \Lambda_t} \right) \Omega_{t-1}^j - (1 - \delta^j)\Omega_t^j \right) k_t^j + \frac{Q_t^{X^j} k_t^j}{P_t} \left(\frac{\partial \Gamma_t}{\partial k_t^j} \right),\tag{29}$$

where ψ_t^j is the real marginal cost. The right-hand sides of (27) and (28) are, respectively, the wage bill and total expenditure on material inputs in sector j. The right-hand side of (29) is the total opportunity cost (net of capital gains) of the capital stock in sector j plus a term that represents the net cost of increasing the current capital stock. Jorgeson's expenditure data may be interpreted as the empirical counterpart of the right-hand side of these equations (see Jorgenson and Stiroh, 2000). Although the data set does not contain observations on $\psi_t^j y_t^j$, it is possible to construct estimates of α^j, ν^j, and γ^j as follows. For a given year, use two of the following three ratios: (27)/(28), (27)/(29) and (28)/(29),[14] and the condition $\alpha^j + \nu^j + \gamma^j = 1$, to obtain a system of three equations with three unknowns. The unique solution of this system delivers an observation of the production function parameters for that year. The estimates of α^j, ν^j, and γ^j are the sample averages of the yearly observations and their standard deviations are $\sqrt{\sigma^2/T}$ where $T = 39$ is the sample size and σ^2 is the variance of the yearly observations. These estimates are reported in Table 1 and indicate substantial heterogeneity in capital, labor and material intensities across sectors. For example, mining is very intensive in capital; construction, agriculture and manufacturing are intensive in materials but not in capital; and services are equally intensive in labor and materials. This heterogeneity is quantitatively important and statistically significant. That is, the difference in parameter estimates across sectors is numerically large and the null hypothesis that α, ν

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used for consumption and production in steady state.

[13]In deriving equation (29) from first-order condition for k_{t+1}^j, we exploit the assumption of rational expectations. Thus, strictly speaking, this equation holds up to a serially uncorrelated forecast error with zero mean.

[14]Note that only two of these three ratios are linearly independent.

and γ are the same in all sectors would be rejected by the data.

The SMM estimates of the model parameters are reported in Table 3. These results are based on a restricted version of the model where 1) the price-adjustment-cost parameters in agriculture, mining and construction are assumed to be the same, and 2) the capital-adjustment-cost parameters in all sectors are also assumed to be the same. These two restrictions were tested using LM tests. Since the p-values were 0.096 and 0.106, respectively, the restrictions would not be rejected by the data at the 5 per cent significance level.[15] The moments included in the loss function (24) are the variances and autocovariances of the variables, and the covariance between the nominal interest rate and the other variables one quarter ahead. The first set of moments allows us to exploit the information contained in the volatility and persistence of the data series. The second set of moments is included because this project is concerned specifically with the interaction between monetary and real variables. Sensitivity analysis indicates that results are robust to using other moments.

The SMM estimates indicate heterogenous price rigidity at the sectoral level. The hypothesis that price rigidity is the same in all sectors is strongly rejected by a Wald test (p-value < 0.01). The hypothesis that $\phi = 0$ can be rejected for services and durable manufacturing, but it cannot be rejected for the other sectors. Since $\phi = 0$ corresponds to the case of flexible prices, this result indicates that price flexibility may be a reasonable approximation in all sectors of the U.S. economy, except for services and durable manufacturing.

These results are in qualitative agreement with micro evidence for the U.S. (Bils and Klenow, 2004) and various European countries. See, for example, Alvarez and Hernando (2004) for Spain, Baudry et al. (2004) for France, Hoffmann and Kurz-Kim (2004) for Germany, Veronese et al. (2004) for Italy, and Vilmunen and Laakkonen (2004) for Finland. Using final goods and services that enter the Consumer Price Index in their respective countries, these researchers typically find heterogeneous price stickiness, more frequent price adjustments for goods than for services, and for nondurable goods (including energy and agricultural products) than for durable goods.[16] This paper confirms their results using an empirical approach that exploits the structure of a fully-specified general equilibrium model and the cross-sectional variation in sectoral inflation rates.

Quantitatively, the estimates here indicate a larger difference between the price rigidity of services and goods than that reported in some of the earlier micro studies. There are two possible explanations for this result. First, although this paper does not model explicitly

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[15]Note, however, that the first restriction would be marginally rejected at the 10 per cent level.

[16]There is also substantial heterogeneity within these broad categories. For example within services, price adjustments are much more frequent for transportation (which includes air travel) than for health services and rents. Cecchetti (1986) and Kashyap (1995) report heterogeneity even within narrowly defined good categories like magazines and shoes sold by catalog.

the housing decision, rental housing is included in the service sector for the purpose of computing the households' expenditure shares. Hoffmann and Kurz-Kim (2004, p. 22) report that including housing rents in their sample increases the overall duration of price spells from 16 to 21 months in Germany. Second, the estimates in this paper are based on both final and intermediate goods. Carlton (1986) studies U.S. micro data on firm-to-firm transactions of intermediate goods and finds long-term relations between buyer-seller pairs and larger price rigidity than that found, for example, by Bils and Klenow (2004) using final goods alone. This is important because data from the Input-Output accounts show that services is the largest producer of intermediate goods in the U.S. economy. In particular, services account (on average) for 36 per cent of the material-input expenditures by other sectors, and for 74 per cent of the expenditures by services itself.

The capital adjustment cost parameter is estimated to be 10.93 (1.94). In order to give meaning to this estimate and to allow its comparison with estimates based on other functional forms, it is useful to compute the elasticity of investment with respect to the price of installed capital. The elasticity implied by this estimate is 4.40 (0.78).[17] This value is much larger than the estimates of 0.34 and 0.28 reported by Kim (2000) and Christiano, Eichenbaum, and Evans (2005), respectively, but is smaller than the value of 15 used, for example, by Baxter and Crucini (1993) to calibrate a Real Business Cycle model. Simulations reported below in Table 4 show that this estimate implies an investment volatility of 9.5, which is very similar to that of 10.6 found in U.S. data.

The estimates of the autoregressive coefficients of the shock processes indicate that all shocks are persistent. The estimate of ρ_η is very close to one, perhaps reflecting trends in financial innovation that are not completely removed from the data by quadratic detrending. The estimate of ρ_μ is similar to values found when money growth is estimated using an univariate process (for example, Chari, Kehoe and McGrattan, 2000).

The overidentification restrictions of the model are tested using a J test. Since the p-value is less than 0.001, the restrictions are rejected at standard significance levels. However, this result must be interpreted with caution because, as is well known, the actual size of this test in small samples far exceeds the nominal size and, consequently, the test rejects too often (see Burnside and Eichenbaum, 1996, and Christiano and den Haan, 1996).

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[17]The elasticity is computed as $1/(\delta\chi)$ using a depreciation rate of 0.0208. This depreciation rate corresponds to an economy-wide rate computed as the weighted average of sectoral depreciation rates.

4 Properties of the Estimated Model

In order to understand better the properties the estimated multi-sector model, this section examines the responses of sectoral and aggregate variables to a monetary policy shock, computes the variance decomposition, volatility and persistence of these variables, compares the multi-sector model with a standard DSGE model that imposes symmetry across sectors, studies the sectoral reallocation of labor following a monetary policy shock, and computes a measure of price rigidity at the aggregate and sectoral levels.

4.1 Responses to a Monetary Policy Shock

Consider an experiment where, starting at the deterministic steady state, the economy is subjected to an unexpected, temporary increase in the growth rate of the money supply of 1 per cent. Then, the growth rate returns to its steady state at the rate ρ_μ. Figure 1 plots the dynamic responses of various aggregate and sectoral variables following this monetary policy shock.

The shock generates a rise in aggregate demand that causes aggregate output to increase (see Panel A). However, this increase is not evenly spread across sectors. In particular, output in construction, durable manufacturing and services increase proportionally more than in the other sectors (see Panel B). The initial increases in these three sectors are 4, 3 and 2.1 per cent, respectively, while in the other sectors they are all approximately 1 per cent. The output increase in services reflects the usual mechanism whereby the monopolistically competitive producer of a sticky-price good partially accommodates an increase in demand by raising its output. The output increase in construction takes place despite the fact that its price is flexible and is due to the input-output structure of the economy. Firms in services and other sectors (see below) increase their current output but also their demand for investment goods in order to build up their capital stock and meet future demand. Since the production of investment goods is heavily concentrated in construction and durable manufacturing, the output increase in these two sectors is large. In the durable-manufacturing sector this increase is due to both monopoly power in the presence of nominal frictions, and input-output effects.

Although prices in agriculture, mining and nondurable manufacturing are flexible and these sectors do not produce capital goods, their output rises persistently as a result of the current and future output increases in construction, services and durable manufacturing (12, 12 and 15 per cent, respectively, of their material-input expenditures go to these sectors).[18]

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[18]Authors' calculations based on the 1992 U.S. Input-Output accounts.

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In summary, the output effects of a monetary policy shock arise from price stickiness in services and durable manufacturing, and are transmitted to the other sectors via the input-output structure of the economy. The input-output structure is crucial in generating a large response in the investment-good producers and positive output comovement across sectors following a monetary policy shock.

Ohanian, Stockman and Kilian (1995) construct a two-sector model without input-output interactions. One sector has a flexible price and the other fixes its price one period in advance. Following a monetary policy shock, the relative price of the flexible-price good raises and, conversely, that of the sticky-price good decreases. This change in relative prices induces a substitution effect in consumption that leads to an output decrease in the flexible-price sector and an increase in the sticky-price sector. Thus, sectoral outputs are negatively correlated. Barth and Ramey (2001), Dedola and Lippi (2003), and Peersman and Smets (2005) use VAR analysis to study the output effects of monetary policy shocks on different manufacturing industries. As in this paper, they also find positively-correlated output responses across industries, and quantitatively larger responses on the part of durable good producers, which they interpret as evidence for the conventional cost-of-capital channel of monetary policy transmission.[19]

Panels C and D plot the responses of hours worked at the aggregate and sectoral levels, respectively. These responses primarily reflect the increase in labor demand on the part of firms, and they follow the same pattern as the output responses reported above. Thus, the sectoral responses of hours worked in constructions, durable manufacturing and services are larger than in the other three sectors. The relative magnitudes of their initial responses are similar to those of output, except for services which is the most labor-intensive sector in the economy. The responses of aggregate and sectoral real wages are plotted in Panels E and F, respectively.[20] The effect of a monetary policy shock on the aggregate wage is relatively persistent, and there is substantial heterogeneity in the response of sectoral wages, with wages in construction, durable manufacturing and services being the most sensitive to this shock.

The dispersion of sectoral hours and wages is less than the dispersion of sectoral outputs at all horizons. For example, the ratio of the standard deviation of sectoral wages to that of

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[19]These authors also find that industries where small firms are more prevalent tend to react more strongly to monetary policy shocks. This finding suggest that financial frictions may also play an important role.

[20]The aggregate real wage is measured by the index $w_t/P_t = \left(\sum_{j=1}^{J} \left(w_t^j/P_t \right)^{1+\varsigma} \right)^{1/(1+\varsigma)}$. This index has the property that $\sum_{j=1}^{J} w_t^j n_t^j = w_t N_t$.

sectoral outputs is only 0.61 in the quarter at which the shock takes place. This result is due in part to the assumption of a preference for diversity in the household's labor supply, which acts as a friction to the reallocation of hours across sectors. As an example, consider the counterfactual assumption that $\varsigma = 2$, meaning that hours worked across sectors are better substitutes than implied by the empirical work in Horvath (2000), where $\varsigma \approx 1$. In this case, the ratio reported above decreases to 0.39. In the limit, as $\varsigma \to \infty$, hours worked in each sector become perfect substitutes, wages in all sector are equalized, and this ratio would be zero. In terms of hours, the increase in substitutability of labor supply across sectors associated with a larger value of ς means that the sectoral dispersion of hours is increasing in ς. These results reflect some degree of labor mobility across sectors and are consistent with earlier findings by Davis and Haltiwanger (2001) who report reallocative effects of monetary policy shocks in U.S. manufacturing.

A monetary policy shock leads to an increase in aggregate consumption and substantial changes in the composition of household consumption (see Panels G and H). The overall effect of the monetary policy shock is largest for manufactured goods (both durable and nondurables) and services. Except for construction, the initial effects are all positive. The consumption of construction decreases on impact and reaches its steady state non-monotonically from below. The dynamics of sectoral consumption reflects the role of relative prices in the economy's adjustment following a shock. To see this, note the path of relative prices in Panel J. The relative price of services declines because its nominal price is sticky. In contrast, the relative price of the other goods rises because their nominal prices are more flexible. The largest increases in relative prices are in construction and mining. From Panels H and J, it is clear that the increase in household consumption is smaller for goods whose relative prices rise the most following a monetary policy shock. Thus, the temporary change in the composition of the consumption bundle simply reflects intratemporal substitution by households.

These impulse-responses are roughly in line with VAR evidence reported in Erceg and Levin (2002). Following a decrease in the U.S. Federal Funds Rate, the consumption of durable goods, residential structures, business equipment and business structures all increase. In the case of the latter two, the response is sluggish and becomes statistically different from zero only after three and seven quarters, respectively. In our multi-sector model, the firms' demand for durables and structures, and the households' demand for durables increase immediately following the monetary policy shock. However, the households' demand for structures decreases, while it increases in Erceg and Levin's VAR. As pointed out above, the reason is that the consumption demand for an individual good is primarily a function of its relative price. Since, construction prices are relatively flexible and there is strong demand

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on the part of firms, its relative price rises steeply and households' demand falls.

Panels K and L plot the response of CPI and sectoral inflation rates to the monetary policy shock. In all cases, the rates increase following the shock and then return monotonically to their steady-state values. Inflation in services increases the least following a monetary policy shock but is also the most persistent. In contrast, inflation in construction and durable manufacturing increase the most but return fairly rapidly to their steady state. This observation is also true for productivity and money demand shocks (not reported). Since the share of services in the CPI is approximately one-half, this means that the dynamics of aggregate inflation at horizons of a year or less are jointly determined by service and non-service sectors. However, since inflation in non-service sectors return much faster to the steady state, the aggregate dynamics at horizons beyond a year are mostly determined by service inflation.

Finally, the response of the real interest rate is plotted in Panel I. The drop in the real rate is substantial and persistent. However, it is clear from panels I and K, that the response of the nominal interest rate (not shown) would be positive and relatively muted. Hence, as in standard sticky-price models, the multi-sector model also fails to produce a liquidity effect. The reason is that the estimated money growth process is highly autocorrelated. Thus, following a monetary policy shock, expected inflation increases by a magnitude that is slightly larger than the decrease in the real interest rate. It follows that the net effect of the monetary shock on the nominal interest rate is quantitatively small and positive.

4.2 Variance Decomposition

One way to evaluate the relative importance of monetary policy shocks in explaining the volatility of aggregate and sectoral variables is to compute their variance decomposition. This entails the calculation of the proportion of the conditional variance of the forecast error at different horizons that is attributable to the monetary policy shock. As the horizon increases, the conditional variance of the forecast error of a given variable tends to the unconditional variance of that variable. Results are reported in Figure 2 for forecast horizons of one to twenty quarters ahead, and in Table 3 for the infinite horizon.

Regarding aggregate variables, monetary policy shocks account for most of the conditional variance of output and consumption at horizons of less than a year, but only for 36 and 40 per cent, respectively, in the long run. The same pattern is observed for investment, where the contribution of this shock decreases (non-monotonically) from about 30 per cent at the one-quarter horizon to 21 per cent in the long run. In contrast, monetary policy shocks explain a larger part of the conditional variances of hours, wages and inflation in the long than in the

short run. For example, the proportion of the conditional variance of CPI inflation that is explained by this shock increases monotonically from 9 per cent at the one-quarter horizon to 19 per cent in the long run.

Regarding sectoral variables, monetary policy shocks explain a substantial part of the conditional variance of output and consumption of durable manufacturing and services, and of hours worked in construction, both in the short and long runs. There is large heterogeneity in the proportion of sectoral wages and investment that is attributable to monetary policy shocks at horizons of less than a year, but these proportions start to converge after about four quarters. Although monetary policy shocks tend to be more important in the short run, their contribution in the long run is quantitatively large in some sectors. For example, they explain 41, 30 and 20 per cent of the unconditional variance of wages in durable manufacturing, nondurable manufacturing and services, respectively, and between 11 (durable manufacturing) and 26 per cent (construction) of the unconditional variance of sectoral investment.

Finally, monetary policy shocks account for less than 15 per cent of the conditional variance of sectoral inflations in the very short run, but (except for services) their contribution increases with the forecast horizon. In the long run, they explain 18 and 32 per cent of the unconditional variance of inflation in construction and durable manufacturing, respectively.

4.3   Sectoral Volatility and Persistence

This section computes the unconditional standard deviations and first-order autocorrelations of aggregate and sectoral variables predicted by the multi-sector model, and compares them with those estimated using aggregate U.S. data and those predicted by a standard DSGE model. By standard DSGE model we mean a model that allows material inputs in the production function but differs from our multi-sector model in that it imposes symmetry across sectors in production and assumes identical consumption weights for all goods. The standard deviations predicted by the two DSGE models are based on simulated series of 175 observations and averaged over 500 replications. The length of the simulated series is equal to the number of observations in the sample of U.S. data.

The parameters used to simulate the multi-sector model are the SMM estimates reported in Tables 1 and 2. The parameters used to simulate the standard DSGE model are the following. The consumption, investment and material input weights (that is, ξ_j, κ_{ij} and ζ_{ij}, respectively) are all set to 1/6. Thus, the Input-Output and Capital Flow Tables of the standard economy are symmetric. The parameters of the production functions are the same for all sectors and are estimated using the same strategy described in Section 3.2 but

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using the sum of expenditures on labor, capital, and material inputs by all sectors. The price-rigidity coefficients and depreciation rates are also the same for all sectors and are computed as the weighted averages of the sectoral estimates reported in Table 2 and the sectoral depreciation rates in Section 3.2, respectively. The values of β, ς, θ and the mean of the technology shock are the same as in the multi-sector model. The other model parameters are those reported in Table 2.

The aggregate and sectoral standard deviations are reported in Table 4. The standard deviations of aggregate variables in the multi-sector and standard models are fairly similar. Notice that for all variables, the standard DSGE model predicts sectoral standard deviations that are identical to the aggregate ones because this model assumes symmetry in production.[21] In contrast, the multi-sector predicts substantial heterogeneity in the volatility of sectoral variables. Comparing the predicted volatilities with those of the sectoral variables for which data are available shows that they are quantitatively similar. Two exceptions are durable consumption and hours worked (notably, in services).

The model counterfactually predicts that the households' consumption of nondurable manufactured goods is more volatile than that of durable goods. In U.S. data, the standard deviations are 3.66 and 8.98, respectively, but in the model they are 4.55 and 2.95, respectively. This discrepancy is due to the fact that the theoretical model abstracts from consumption durability and, consequently, sectoral household demand depends primarily on relative prices. Thus, the larger volatility of inflation in nondurable than durable manufacturing translates into more volatile consumption of the former compared with the latter.

The multi-sector model predicts substantial volatility in sectoral hours and wages. The volatility of hours worked is larger in the model than in the data for construction, nondurable manufacturing and, specially, services.[22] This suggests that it may be fruitful to incorporate labor market frictions, such as labor-adjustment costs and sector-specific skills, in multi-sector models. The output of construction and agriculture are the most volatile, while that of services is the least volatile. The volatility of construction output is 3 times larger than that of services and aggregate output. On the other hand, investment by the construction sector is the least volatile, perhaps because this sector is the least capital-intensive in the U.S. economy.

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[21]The only exception is output because sectoral output is measured by gross output while aggregate output is measured by value added. The same caveat applies to estimates of the first-order autocorrelation. The volatility and autocorrelation of sectoral output are 3.68 and 0.77, respectively, for all sectors.

[22]These results should be interpreted with caution because the notion of hours and wages in the model and the data are not exactly the same. In the model, hours worked are a share while in the data they are average weekly hours of production workers. It is not possible to construct a better data equivalent because data on hours worked in agriculture are missing from the BLS database. The measure of wages in the data is average weekly earnings of production workers and may include compensation other than wages.

Comparing the predicted sectoral inflation volatilities and their empirical counterparts indicates that their magnitudes are quantitatively similar, with inflation in agricultural goods being more volatile than that of manufactured goods. The model also predicts large volatility in the inflation rate of mining goods. Industry-level data for mining are not available for the complete sample, but this prediction of the model accords well with the observed volatility in the price inflation of various mineral commodities.

The aggregate and sectoral autocorrelations are reported in Table 5. The multi-sector model generates predictions for the persistence of aggregate and sectoral variables that are roughly in line with the data, except for hours worked. In particular, notice the large heterogeneity in the predicted persistence of sectoral inflation rates, and their similarity to the values found in the data.

4.4 Comparison with the Standard Symmetric Model

Results regarding the predicted standard deviations and autocorrelations reported in Tables 4 and 5 indicate that the multi-sector and standard DSGE models differ only modestly in their aggregate predictions. This result is explored further in this Section by comparing the impulse responses of aggregate variables to a monetary policy shock under both models. Figure 2 reproduces the responses of aggregate output, consumption, hours worked, real wages, CPI inflation, and the real interest rate following a monetary policy shock that were previously reported in Figure 1 for the multi-sector model, and plots the corresponding responses for the standard model.

The responses from both models are very similar for output, consumption, and real wages. There are quantitatively small differences in the initial response of inflation and the real interest rate, but after four quarters the predictions of both models coincide exactly. The only appreciable difference between the two models is in the dynamic response of aggregate hours. While the initial response is almost the same in the multi-sector and standard models, the converge to the steady state is somewhat faster in the former than in the latter.

Overall, these results and those in Tables 4 and 5 indicate that modeling the heterogeneity of the different production sectors in the economy does not modify in a substantive manner the aggregate implications of DSGE models that impose symmetry. This result is important because it suggests that literature that imposes symmetry across goods may still provide a reasonable description of the behavior of aggregate variables.[23]

The reason for this result is that the multi-sector model permits the reallocation (al-

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[23]A similar result is reported by Balke and Nath (2003) in a calibrated multi-sector with no capital and perfect labor mobility across sectors.

beit imperfect) of labor and capital across sectors. The reallocation of labor depends on the degree of substitutability of hours worked in the utility function of the representative household. Also, although capital is sector-specific in the multi-sector model in that each sector uses a different nonlinear combination of investment inputs, the composite X_t^j can be unbundled and its parts sold to other sectors in a frictional market. Thus, in the presence of moderate frictions in the movement of capital and labor across sectors, the aggregates of a multi-sector economy behave in similar manner to those generated by a standard model that ignores heterogeneity in production.[24]

4.5 Sectoral Versus Aggregate Price Rigidity

The multi-sector DSGE model also allows us to compare price rigidity at the sectoral and aggregate levels. A distinction is made between *ex-ante* price rigidity, which is measured by the price-adjustment-cost parameters reported in Table 2, and *ex-post* price rigidity, which depends on both these parameters and the optimal pricing behavior of firms in each sector. This Section computes *ex-post* price rigidity at the sectoral and aggregate levels as the ratio of price-adjustment costs to output. By construction, price-adjustment costs are zero in steady state, but estimates of their average magnitude outside steady state can be computed by means of simulation. The results below are based on simulated series of 175 observations averaged over 500 replications.

For the sectoral estimates, it is easy to see from the definition of dividends in Equation (16) that the ratio of adjustment costs to output is simply Φ_t^j. For the aggregate estimate, the ratio is

$$
\frac{\sum\limits_{j=1}^{J} \Phi_t^j p_t^j \left(c_t^j + \sum\limits_{i=1}^{J} x_{j,t}^i + \sum\limits_{i=1}^{J} h_{j,t}^i \right)}{\sum\limits_{j=1}^{J} Y_t^j}, \tag{30}
$$

where $\sum\limits_{j=1}^{J} Y_t^j$ is aggregate nominal output and is defined in (23).

Estimates reported in Table 6 indicate that sectoral price-adjustment costs vary between 0.011 and 0.058 per cent of output in mining and services, respectively. On the other hand, the aggregate price-adjustment costs are 0.061 per cent of GDP. This aggregate estimate is larger than each of the sectoral estimates and than their weighted average, which is 0.04. This means that *ex-post* price rigidity is larger at the aggregate than at the sectoral level.

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[24]In related work, Carlstrom, Fuerst, Ghironi and Hernandez (2005) construct and calibrate a two-sector model with heterogenous price rigidity and labor immobility across sectors, and report additional persistence (vis-a-vis the one-sector model) stemming from relative price dynamics.

In order to understand this result, note that firms pay price-adjustment costs on all transactions regardless of whether the good is used for final or intermediate consumption. However, aggregate output in the model, as in the U.S. National Income and Product Accounts, is measured by value added, which avoids double counting by excluding the transactions of intermediate goods. Since the numerator in (30) is the sum of all sectoral price-adjustment costs, but the denominator is only the sum of all sectoral values added, the aggregate ratio is larger than the weighted average of the sectoral estimates.

5   Discussion

This paper studies the effects of monetary policy through the lens of a multi-sector model. In contrast to earlier sticky-price models that impose symmetry across sectors, this analysis models explicitly the heterogeneity in production and frictions that are a prominent feature of the data. The paper shows that although sectoral heterogeneity makes quantitatively little difference for the dynamics of aggregate variables, modeling the input-output structure of the economy is crucial in understanding the sensitivity of different sectors to monetary policy shocks, as well as the sectoral reallocation of productive resources. Econometric results indicate subtantial heterogeneity in price rigidity across sectors, and that services and, to a lesser extent, durable manufacturing account for most of the rigidity observed at the aggregate level. Due to the input-output structure, monetary policy shocks have large effects even on flexible-price sectors.

The parameter values are estimated so as to minimize the distance between the moments of artificial series generated by the multi-sector model and those computed from a mix of aggregate and sectoral U.S. data. Yet, there are a few dimensions along which the multi-sector model fails to match the data, namely the volatility and persistence of aggregate wages and hours worked, and the volatility of durable consumption. Hence, in future work, we intend to incorporate explicit frictions in the labor market, such as wage stickiness and labor-adjustment costs.

Table 1. Estimates of Production Function Parameters

Sector	α	ν	γ
Agriculture	0.142*	0.261*	0.597*
	(0.005)	(0.006)	(0.006)
Mining	0.380*	0.243*	0.377*
	(0.009)	(0.004)	(0.011)
Construction	0.052*	0.394*	0.554*
	(0.001)	(0.004)	(0.005)
Durables	0.100*	0.321*	0.579*
	(0.001)	(0.003)	(0.002)
Nondurables	0.113*	0.225*	0.662*
	(0.004)	(0.002)	(0.006)
Services	0.222*	0.399*	0.379*
	(0.004)	(0.003)	(0.007)

Notes: α, ν and γ are, respectively, the exponents of capital, labor and material inputs in the sectoral production functions. The numbers in parenthesis are standard errors. The superscript $*$ denotes the rejection of the hypothesis that the true parameter is zero at the 5 per cent significance level.

Table 2. SMM Estimates

Parameter	Estimate
$\phi^{durables}$	13.51*
	(5.25)
$\phi^{nondurables}$	2.47
	(1.55)
$\phi^{services}$	98.55*
	(34.89)
ϕ^{others}	0.65
	(0.77)
χ	10.93*
	(1.94)
ρ_z	0.67*
	(0.09)
ρ_μ	0.45*
	(0.12)
ρ_η	0.99*
	(0.01)
σ_z	0.10*
	(0.04)
σ_μ	0.005*
	(0.001)
σ_η	0.004
	(0.004)

Notes: ϕ^{others} is the price-adjustment-cost parameter for agriculture, mining and construction estimated under the restriction that it is the same in the three sectors. See the notes to Table 1.

Table 3. Percentage of the Unconditional Variance Due to Monetary Policy Shocks

Sector	Output	Consumption	Investment	Hours	Wages	Inflation
Aggregate	36.14	40.02	21.05	21.66	20.04	18.85
Agriculture	1.76	1.15	20.65	3.10	19.71	4.93
Mining	2.26	1.59	25.94	7.34	21.31	17.99
Construction	7.33	1.62	14.30	20.12	24.22	18.88
Durables	24.90	9.71	11.06	13.74	41.38	32.32
Nondurables	5.07	4.14	19.71	4.48	29.67	9.48
Services	44.39	48.16	21.31	4.94	19.87	7.14

Table 4. Sectoral Volatility

Sector	Output	Consumption	Investment	Hours	Wages	Inflation
			A. U.S. Data			
Aggregate	3.74	3.40	10.59	0.55	4.15	0.80
Agriculture	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	2.72
Mining	*n.a.*	*n.a.*	*n.a.*	1.87	2.91	*n.a.*
Construction	*n.a.*	*n.a.*	*n.a.*	1.31	7.14	*n.a.*
Durables	*n.a.*	8.98	*n.a.*	1.69	3.44	0.99
Nondurables	*n.a.*	3.66	*n.a.*	1.11	3.18	1.68
Services	*n.a.*	3.07	*n.a.*	0.38	4.07	*n.a.*
			B. Multi-Sector Model			
Aggregate	3.06	2.44	9.48	2.30	6.11	0.49
Agriculture	5.97	6.91	17.39	1.83	2.67	2.52
Mining	4.90	4.51	10.89	1.22	2.69	1.84
Construction	11.15	6.07	5.88	3.79	5.44	2.35
Durables	4.44	2.95	9.33	3.40	3.40	0.71
Nondurables	4.33	4.55	8.83	1.63	2.30	1.28
Services	3.43	2.40	10.96	7.00	6.15	0.33
			C. Standard Model			
Aggregate	2.78	2.29	8.02	6.58	3.85	0.30

Notes: *n.a.* stands for not available. The sample used to compute the statistics for U.S. data is 1959:2 to 2002:4. The exceptions are aggregate hours and wages, and the sectoral hours and wages for services that were computed using data from 1964:1 to 2002:4. The standard model predicts sectoral standard deviations that are identical to the aggregate ones reported in the last row of this Table.

Table 5. Sectoral Persistence

Sector	Output	Consumption	Investment	Hours	Wages	Inflation
			A. U.S. Data			
Aggregate	0.96	0.97	0.90	0.75	0.95	0.72
Agriculture	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	−0.06
Mining	*n.a.*	*n.a.*	*n.a.*	0.80	0.80	*n.a.*
Construction	*n.a.*	*n.a.*	*n.a.*	0.44	0.96	*n.a.*
Durables	*n.a.*	0.93	*n.a.*	0.88	0.92	0.75
Nondurables	*n.a.*	0.96	*n.a.*	0.81	0.95	0.43
Services	*n.a.*	0.95	*n.a.*	0.59	0.95	*n.a.*
			B. Multi-Sector Model			
Aggregate	0.89	0.91	0.85	0.40	0.69	0.48
Agriculture	0.87	0.76	0.88	0.28	0.87	0.05
Mining	0.80	0.74	0.77	0.43	0.89	−0.02
Construction	0.82	0.75	0.85	0.84	0.86	0.03
Durables	0.86	0.91	0.88	0.43	0.73	0.51
Nondurables	0.89	0.87	0.88	0.27	0.90	0.30
Services	0.76	0.91	0.83	0.61	0.69	0.70
			C. Standard Model			
Aggregate	0.89	0.91	0.86	0.63	0.74	0.69

Notes: See the notes to Table 4.

Table 6. Ratio of Price Adjustment Costs to Output

Sector	Ratio (in percent)
Aggregate	0.0608
Agriculture	0.0206
Mining	0.0110
Construction	0.0179
Durables	0.0348
Nondurables	0.0205
Services	0.0576

References

[1] Altig, D., Christiano, L. J., Eichenbaum, M., and Linde, J., (2005), "Firm-Specific Capital, Nominal Rigidities and the Business Cycle," NBER Working Paper No. 11034.

[2] Alvarez, L. J. and Hernando, I., (2004), "Price Setting Behaviour in Spain: Stylized Facts Using Consumer Price Micro Data," Bank of Spain Working Paper No. 0422.

[3] Aoki, K., (2001), "Optimal Monetary Policy Responses to Relative Price Changes," *Journal of Monetary Economics* 48, 55-80.

[4] Balke, N. S., and Nath, H. K., "Nominal Price Rigidities in a Multisector Model," Southern Methodist University, Mimeo.

[5] Barth, M. J., and Ramey, V. A., (2001), "The Cost Channel of Monetary Transmission," *NBER Macroeconomics Annual* 16, 199-239.

[6] Basu, S. and Fernald, J., (1994), "Constant Returns and Small Markups in U.S. Manufacturing," International Finance Discussion Paper 483.

[7] Baudry, L., Le Bihan, H., Sevestre, P., and Tarrieu, S., (2004), "Price Rigidity: Evidence from the French CPI Micro-Data," European Central Bank Working Paper No. 384.

[8] Baxter, M. and Crucini, M. J. (1993), "Explaining Saving-Investment Correlations," *American Economic Review* 83, 416-436.

[9] Benigno, P., (2004), "Optimal Monetary Policy in a Currency Area," *Journal of International Economics* 63, 293-320.

[10] Bergin, P. and Feenstra, R. (2000), "Staggered Price Setting, Translog Preferences, and Endogenous Persistence," *Journal of Monetary Economics* 45, 657-680.

[11] Bils, M. and Klenow, P. J., (2004), "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy* 112, 947-985.

[12] Blanchard, O. J. and Khan, C. M., (1980), "The Solution of Linear Difference Models Under Rational Expectations," *Econometrica* 48, 1305-1311.

[13] Blanchard, O. J. and Kiyotaki, N., (1987), "Monopolistic Competition and the Effects of Aggregate Demand," *American Economic Review* 77, 647-666.

[14] Burnside, C. and Eichenbaum, M., (1996), "Small-Sample Properties of GMM-Based Wald Tests," *Journal of Business and Economic Statistics* 14, 294-308.

[15] Carlton, D. W., (1986), "The Rigidity of Prices," *American Economic Review* 76, 637-658.

[16] Carlstrom, C. T., Fuerst, T. S., Ghironi, F., and Hernandez, K., (2005), "Relative Price Dynamics and the Aggregate Economy," Boston College, Mimeo.

[17] Cecchetti, S. G. (1986), "The Frequency of Price Adjustment: A Study of the Newsstand Prices of Magazines," *Journal of Econometrics* 31, 255-274.

[18] Clarida, R., Gali, J., and Gertler, M., (2000), "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics* 115, 147-180.

[19] Chari, V., Kehoe, P., and McGrattan, E. (2000), "Sticky Price Models of the Business Cycle: Can the Contract Multiplier Solve the Persistence Problem," *Econometrica*, 68, 1151-1179.

[20] Christiano, L. J. and den Haan, W. J., (1996), "Small-Sample Properties of GMM for Business Cycle Analysis," *Journal of Business and Economic Statistics* 14, 309-327.

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

[22] Davis, S. J. and Haltiwanger, J., (2001), "Sectoral Job Creation and Destruction Responses to Oil Price Changes," *Journal of Monetary Economics* 48, 465-512.

[23] Dedola, L. and Lippi, F. (2003), "The Monetary Transmission Mechanism: Evidence from the Industries of Five OECD Countries," Bank of Italy, Mimeo.

[24] Dixit, A. and Stiglitz, J., (1977), "Monopolistic Competition and Optimum Product Diversity," *American Economic Review* 67, 297-308.

[25] Duffie, D. and Singleton, K. J., (1993), "Simulated Moments Estimation of Markov Models of Asset Prices," *Econometrica* 61, 929-952.

[26] Dupor, B., (1999), "Aggregation and Irrelevance in Multi-Sector Models," *Journal of Monetary Economics* 43, 391-410.

[27] Erceg, C. J. and Levin, A., (2002), "Optimal Monetary Policy with Durable and Non-Durable Goods," European Central Bank Working Paper No. 179.

[28] Gregory, A. and Smith, G., (1991), "Calibration as Testing: Inference in Simulated Macroeconomic Models," *Journal of Business and Economic Statistics* 9, 297-304.

[29] Hoffmann, J. and Kurz-Kim J.-R., (2004), "Consumer Price Adjustment Under the Microscope: Germany in a Period of Low Inflation," Deutsche Bundesbank, Mimeo.

[30] Hornstein, A. and Praschnik, J., (1997), "Intermediate Inputs and Sectoral Comovements in the Business Cycle," *Journal of Monetary Economics* 40, 573-598.

[31] Horvath, M., (2000), "Sectoral Shocks and Aggregate Fluctuations," *Journal of Monetary Economics* 45, 69-106.

[32] Huang, K. and Liu Z., (2004), "Inflation Targeting: What Inflation Rate to Target," *Journal of Monetary Economics,* forthcoming.

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

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

[35] Jorgenson, D. W., and Stiroh, K. J., (2000), "Rising the Speed Limit: U.S. Economic Growth in the Information Age," *Brookings Papers on Economic Activity*, 125-235.

[36] Kashyap, A. K. (1995), "Sticky Prices: New Evidence from Retail Catalogs," *Quarterly Journal of Economics* 110, 245-274.

[37] Kim, J., (2000), "Constructing and Estimating a Realistic Optimizing Model of Monetary Policy," *Journal of Monetary Economics* 45, 329-359.

[38] Lee, B.-S., and Ingram, B. F., (1991), "Simulation Estimation of Time-Series Models," *Journal of Econometrics* 47, 195-205.

[39] McFadden, D., (1986), "A Method of Simulated Moments for Estimation of Discrete Response Models without Numerical Integration," *Econometrica* 57, 995-1026.

[40] Ngai, L. R., and Pissarides, C. A., (2004), "Structural Change in a Multisector Model of Growth," London School of Economics, Mimeo.

[41] Ohanian, L. E., Stockman, A. C., and Kilian, L., (1995), "The Effects of Real and Monetary Shocks in a Business Cycle Model with Some Sticky Prices," *Journal of Money, Credit and Banking* 27, 1210-1234.

[42] Pakes, A. and Pollard, D., (1989), "The Asymptotic Distribution of Simulation Experiments," *Econometrica*, 57, 1027-1057.

[43] Peersman, G. and Smets, F., (2005), "The Industry Effects of Monetary Policy in the Euro Area," *Economic Journal,* forthcoming.

[44] Rotemberg, J. and Woodford, M., (1997), "An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy," *NBER Macroeconomics Annual* 12, 297-345.

[45] Ruge-Murcia, Francisco, J., (2003), "Methods to Estimate Dynamic Stochastic General Equilibrium Models," University of Montreal, CIREQ Working Paper No. 17-2003.

[46] Veronese, G., Fabiani, S., Gattulli, A., and Sabbatini, R., (2004), "Consumer Price Behaviour in Italy: Evidence from Micro CPI Data," Bank of Italy Working Paper No.

[47] Vilmunen, J. and Laakkonen, H., (2004), "How Often do Prices Change in Finland? Micro-Level Evidence from the CPI," Bank of Finland, Mimeo.

[48] Watson, M., (1993), "Measures of Fit for Calibrated Models," *Journal of Political Economy* 101, 1011-1041.

[49] Woodford, M., (2005), "Firm-Specific Capital and the New Keynesian Phillips Curve," NBER Working Paper No. 11149.

[50] Yun, T., (1996), "Nominal Price Rigidity, Money Supply Endogeneity, and Business Cycles," *Journal of Monetary Economics* 37, 345-370.

Figure 1. Impulse Responses to a Monetary Policy Shock

A. Aggregate Output
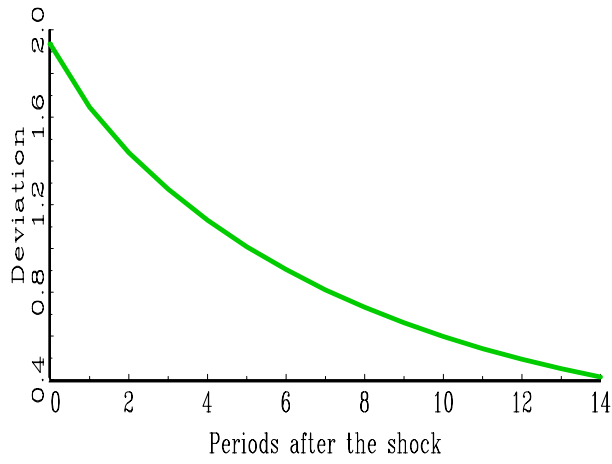
B. Sectoral Output
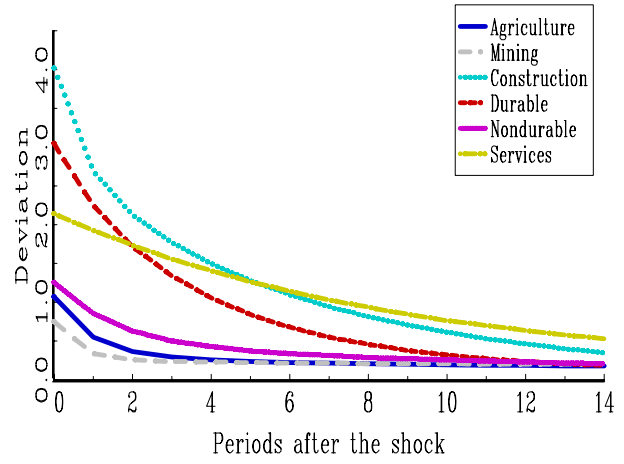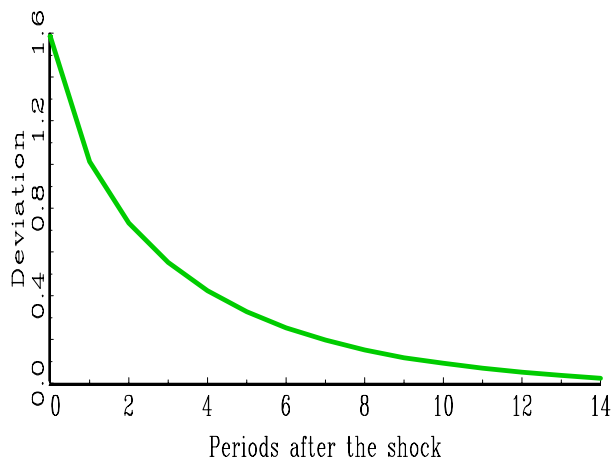
C. Aggregate Hours
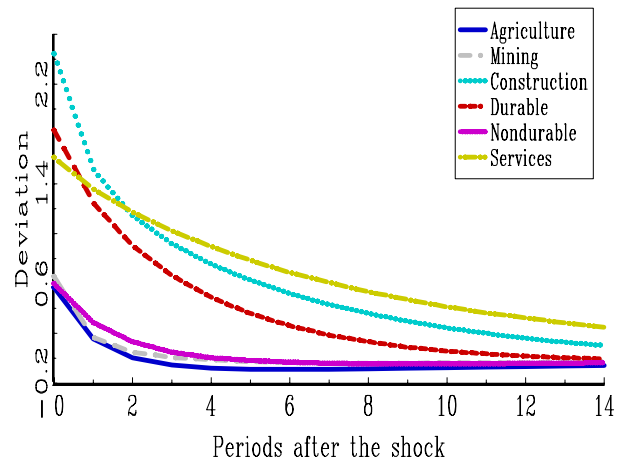
D. Sectoral Hours
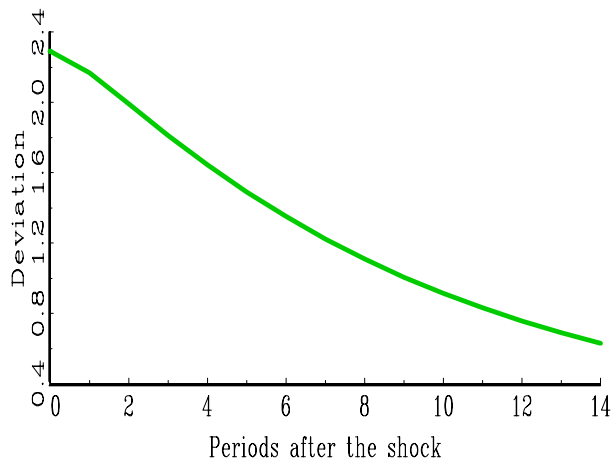
E. Aggregate Wage

F. Sectoral Wages
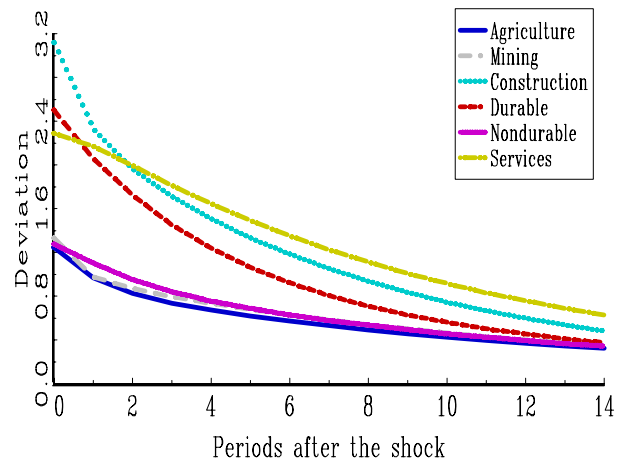
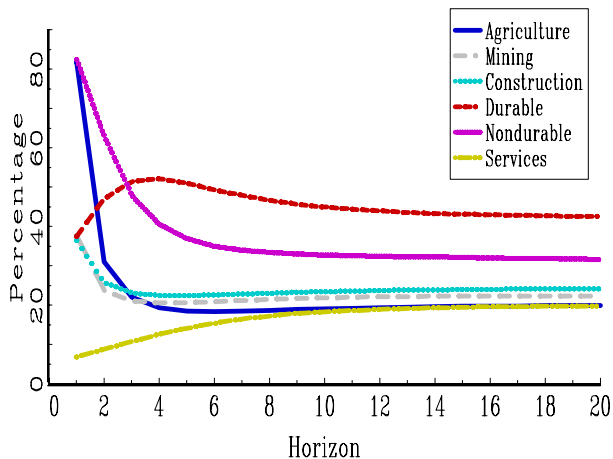# Figure 1. Impulse Responses to a Monetary Policy Shock (cont.)

G. Aggregate Consumption
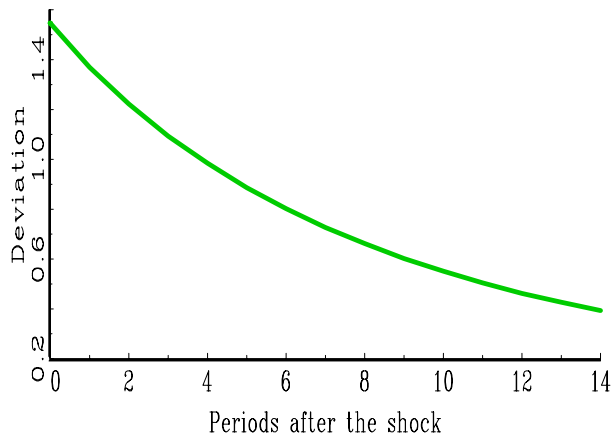
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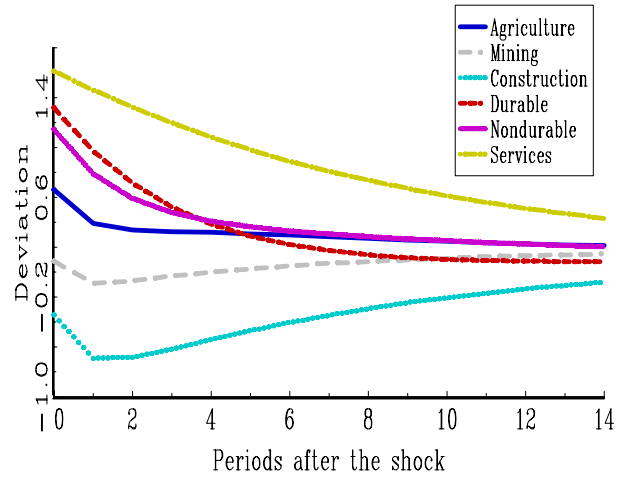
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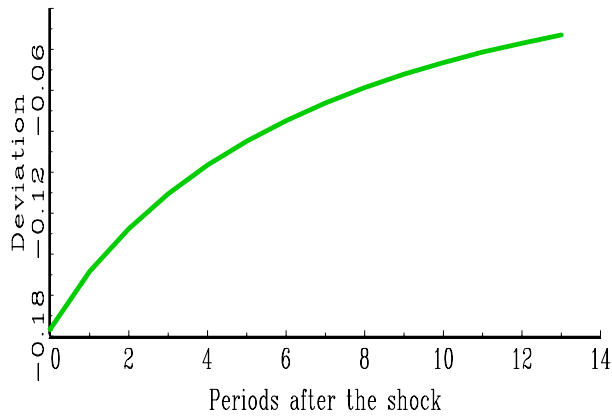
J. Relative Prices
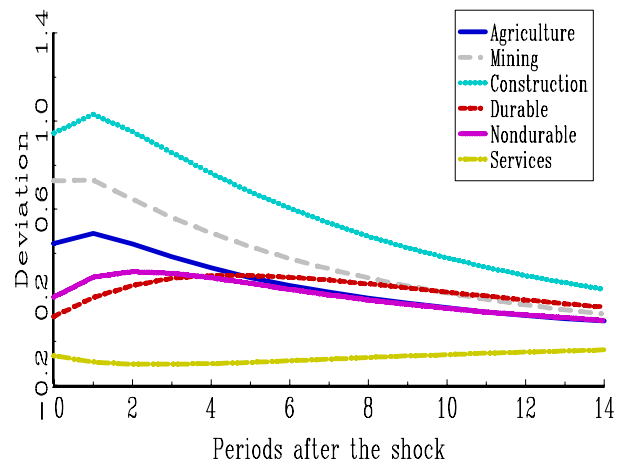
K. CPI Inflation
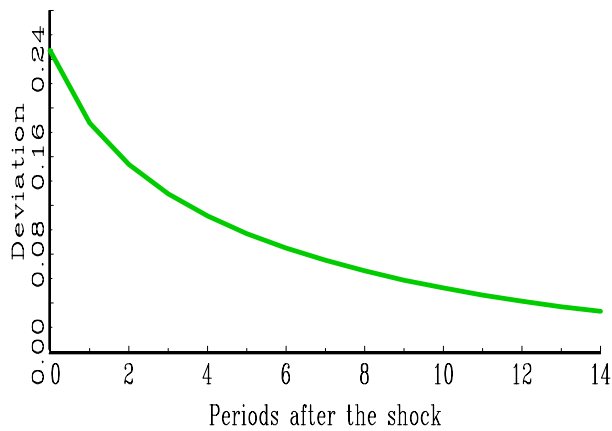
L. Sectoral Inflation
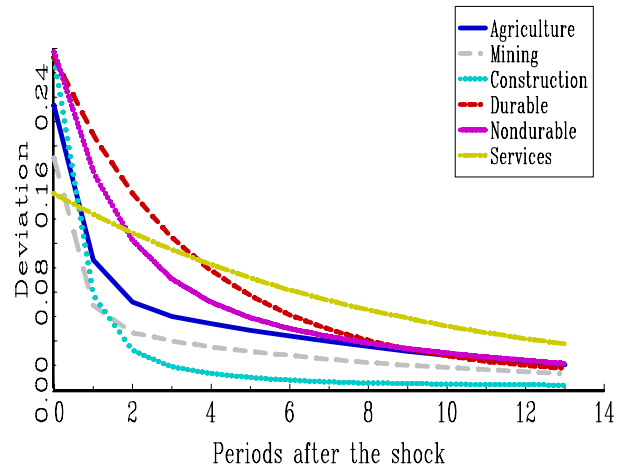
Figure 2. Percentage of the Conditional Variance Due to Monetary Policy Shocks

A. Aggregate Output
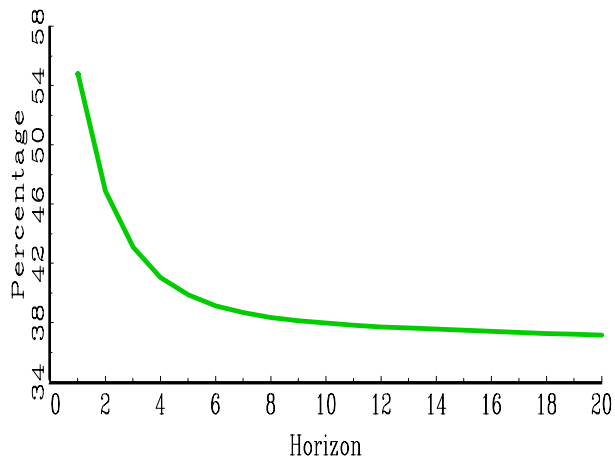
B. Sectoral Output
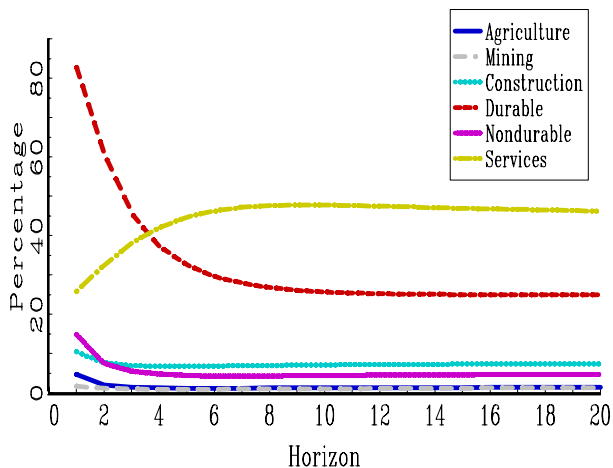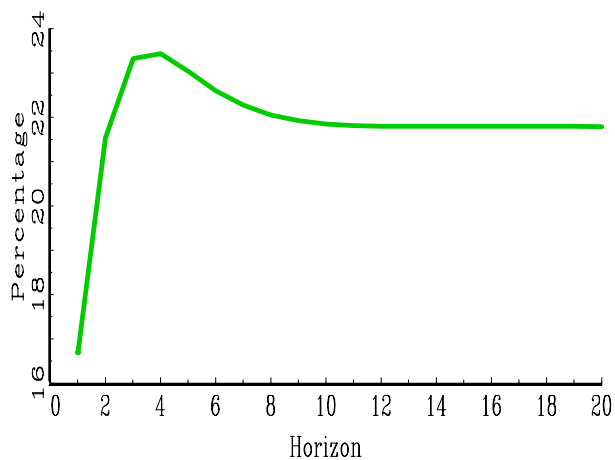
C. Aggregate Hours
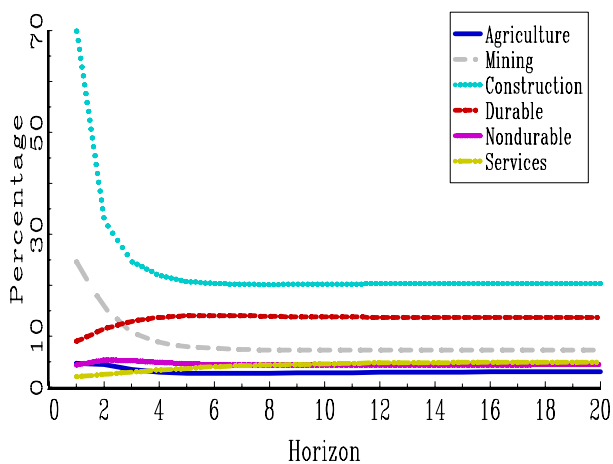
D. Sectoral Hours
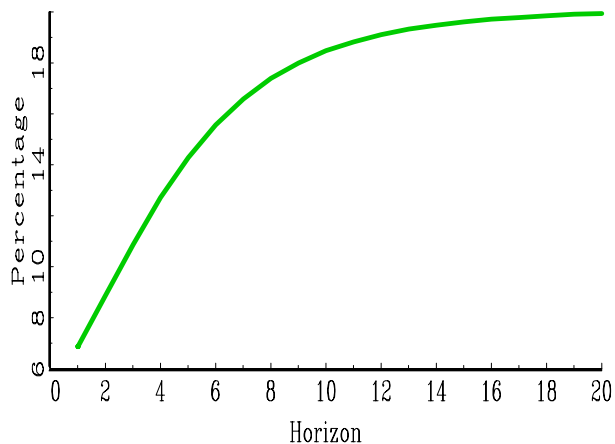
E. Aggregate Wage

F. Sectoral Wages

Figure 2. Percentage of the Conditional Variance Due to Monetary Policy Shocks (cont.)

G. Aggregate Consumption
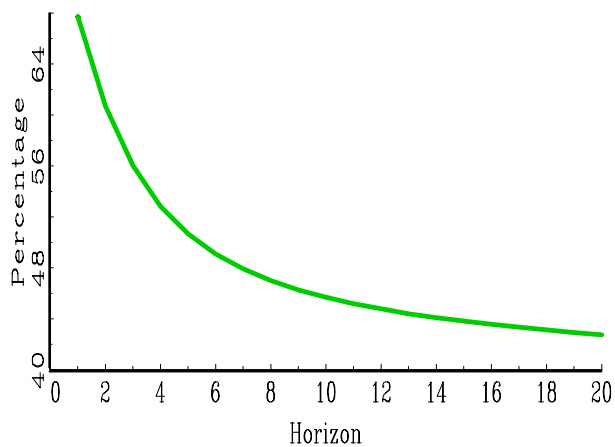
H. Sectoral Household Consumption
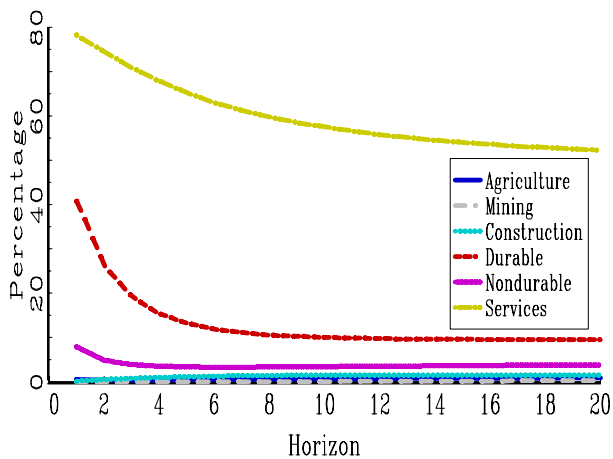
I. Aggregate Investment
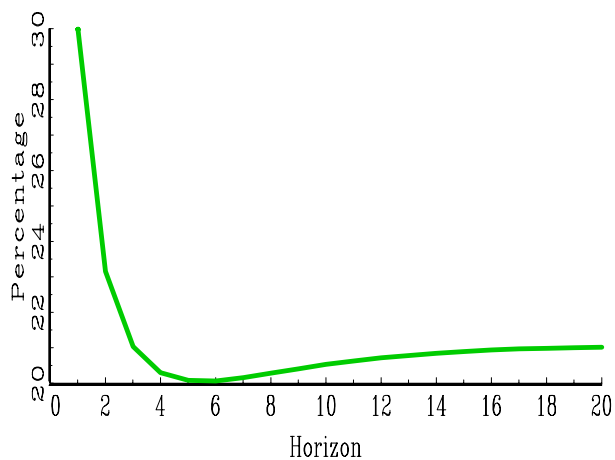
J. Sectoral Investment
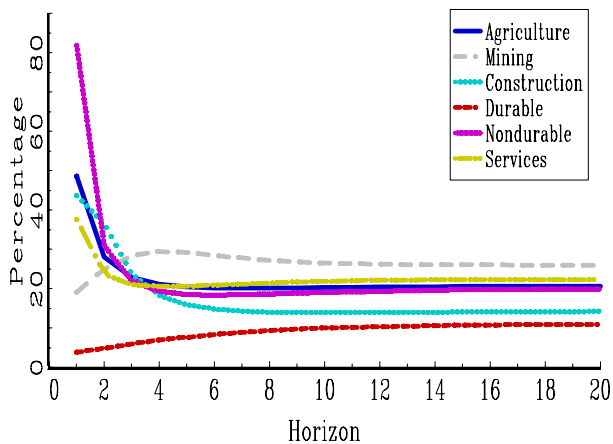
K. CPI Inflation
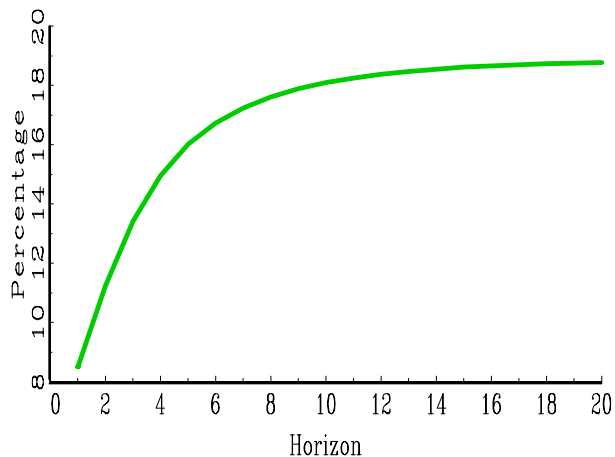
L. Sectoral Inflation
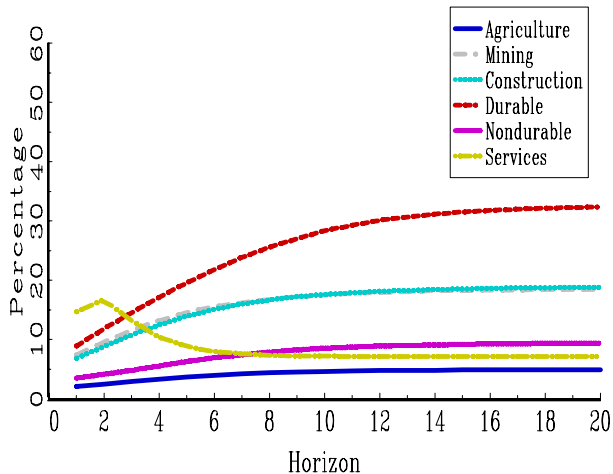
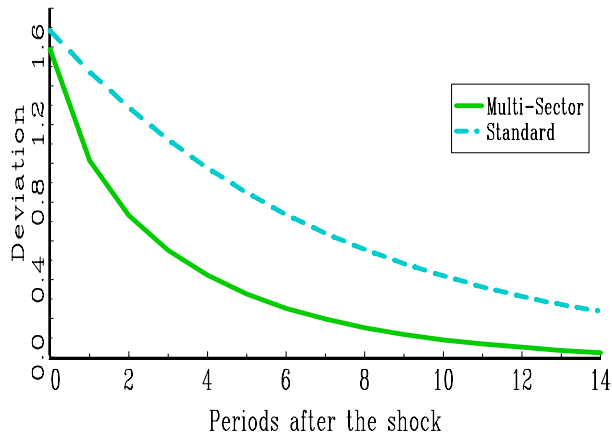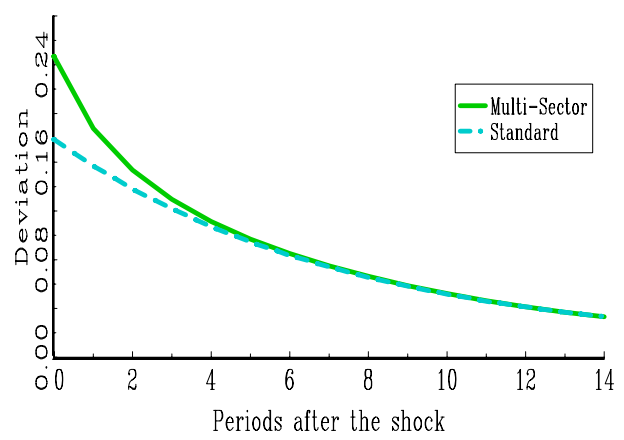# Figure 3. Comparison with the Standard Symmetric Model

A. Sectoral Output
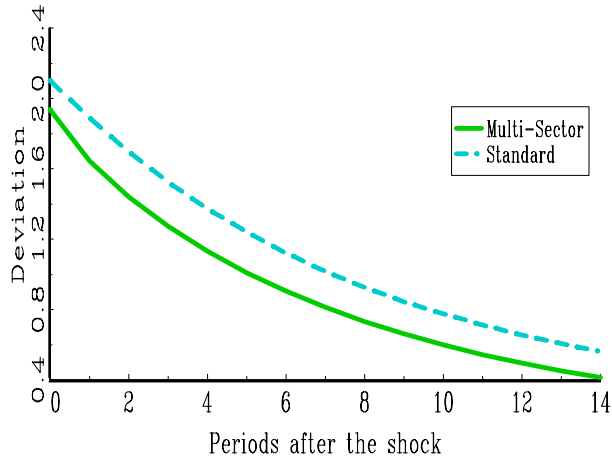
B. Aggregate Consumption
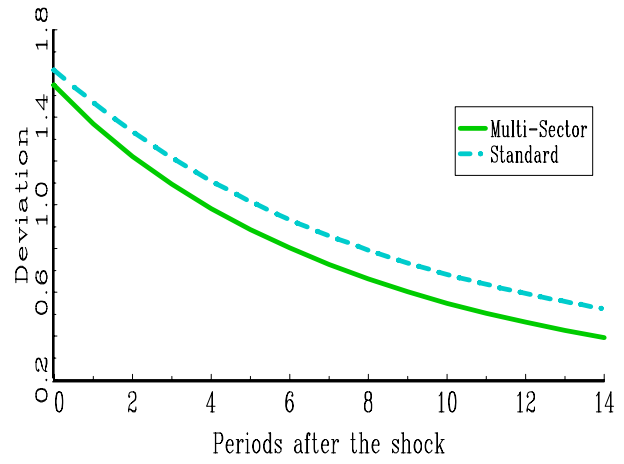
C. Aggregate Hours

D. CPI Inflation

E. Aggregate Wage

F. Real Interest Rate