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Price Setting in a Model with Production Chains: Evidence from Sectoral Data

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Abstract

Reconciling the high frequency of price changes at the micro level and their apparent rigidity at the aggregate level has been the subject of considerable debate in macroeconomics recently. In this paper I show that incorporating production chains in a standard New-Keynesian model replicates two stylized facts about the data. First, sectoral prices respond with significantly different speeds to aggregate shocks. Meanwhile, the responses to sector-specific shocks are similar. Second, the standard price setting models are unable to quantitatively match the amount of monetary non-neutrality observed in the data. I argue, First, that the input-output linkages in production generate different responses to aggregate shocks across sectors. Second, calibrating this model to the US data can create five times more monetary non-neutrality in response to nominal shocks compared to an equivalent homogeneous economy with intermediate inputs. Finally, the model implies that upstream industries respond faster to aggregate shocks compared to downstream industries. I show that this prediction is supported by the data.

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I. Introduction

It is a stylized fact that the frequency of price changes indicates very little nominal rigitdity at the micro level. However, macroeconomic models rely on nominal rigidities at the aggregate level to generate monetary non-neutrality. The accuracy of this assumption in the face of the stylized fact above has been the subject of considerable debate in macroeconomics recently. Models of price adjustment with some type of nominal rigidity, such as menu-costs or Calvo type rigidities, calibrated to match the frequency of individual price changes, fail to deliver aggregate nominal rigidities consistent with typical VAR studies (see, for example, Golosov and Lucas (2007) for an empirical documentation of this fact).[1]

In a recent development, Boivin, Giannoni, and Mihov (2009) (henceforth BGM) offer an explanation for the apparent discrepancy: they decompose price fluctuations into aggregate and sector-specific components and show that sectoral prices appear sticky in response to aggregate shocks whereas they are flexible in response to sector-specific shocks. Therefore, the observed flexibility of disaggregated prices, as reported by Bils and Klenow (2005), Nakamura and Steinsson (2008a), and others, is not necessarily at odds with the results of typical VAR studies.

Furthermore, BGM show that there is significant heterogeneity in the speed of response to aggregate shocks, such as monetary policy shocks, whereas the speed of response of disaggregated prices to own sector-specific disturbances is similar across sectors. For instance, BGM reports an 11% standard deviation of price adjustment (relative to the price level before the shock) across all sectors six months after a monetary policy shock has occurred (average adjustment over the same period is 6%), while following a sector-specific shock nearly all sectors respond fully within the first six months.

The different nature of response of firms to aggregate vs. idiosyncratic shocks can be an explanation for the discrepancy in the frequency of price adjustment at the micro and macro level. But what mechanism causes a differential response to aggregate vs. idiosyncratic shocks? In this paper I explore a possible explanation for this observation. I argue that the existence of a structure which amplifies small nominal rigidities at the firm level could deliver large nominal rigidities at the aggregate level. The particular structure I have in mind is a production chain. Along a production chain, the marginal cost of firms depends on the prices of their material inputs, that is, the prices of other firms in the economy. Therefore, despite individual prices adjusting relatively quickly to changes in their own marginal cost, the accumulation of small lags along the production chain will lead to large lags at the aggregate level. I formalize this idea in a model with a multi-sector economy where firms face Calvo-type nominal rigidities.

An important implication of the model is that the speed of a sector's response to aggregate shocks depends on its position along the production chain, while all sectors, regardless of their position,

[1] Many papers, beginning with Caplin and Spulber (1987), argue this point theoretically. Caballero and Engel (2007) offer a very useful discussion of this literature.

respond quickly to their own sectoral shocks. This is precisely in line with the findings of BGM. Here, I present a multi-sector New Keynesian model incorporating production chains. Different sectors in the economy use inputs with varying intensity. Industries that mainly use labor as their input to production are classified as upstream whereas those heavily dependent on intermediate inputs from other sectors for their production are classified as downstream industries. The model would suggest that upstream industries (such as crude materials and agricultural products) would be the first to respond to aggregate shocks whereas downstream industries (such as consumption goods) would respond much more slowly. I will show that this broad pattern is supported by the data.

An appealing feature of this model is that it generates substantial nominal rigidity at the aggregate level without featuring prices that are too sticky at the micro-level. Nakamura and Steinsson (2008b) emphasize this fact in a multi-sector menu-cost model. They show that adding input-output linkages substantially increases nominal rigidities at the aggregate level. I show in this paper that heterogeneity in the degree of intermediate inputs use increases the non-neutrality even further. Furthermore, a realistic calibration of the model shows that heterogeneity in "inherent" stickiness (captured here by Calvo adjustment frequency) is reinforced by heterogeneity in the material inputs share.[2] Under the most general (and realistic) calibration, the model can amplify the monetary non-neutrality by a factor of five compared to the equivalent economy with intermediate inputs.

A related paper by Mackowiak and Wiederholt (2007) develops a model to address the differential response to aggregate and idiosyncratic shocks. In their model price setting firms decide what to pay attention to subject to a constraint on the information flow. When idiosyncratic conditions are more variable than aggregate conditions, firms pay more attention to idiosyncratic conditions. In their model prices react quickly and by large amounts to idiosyncratic shocks but only slowly and by small amounts to aggregate shocks, which is consistent with the results found in BGM.[3] The model I present here obtains conclusions similar to Mackowiak and Wiederholt (2007) but works through the input-output linkages in production chains.

The paper is organized as follows. In Section II, I present the model and discuss the solution method. In Section III, I calibrate the model. I start from a very spcific case: a two-sector example in which one good is purely an intermediate good and the other purely a consumption good. In developing this example I isolate the effect I am interested in, that is, the differential response of sectoral prices to sector-specific vs. aggregate shocks. I then present a more realistic, 6-sector calibration of the US economy. I relax the assumption of symmetry across sectors in the make-up of consumption and intermediate input goods. I also add heterogeneity in the frequency of

[2] Carvalho (2006) shows that monetary shocks tend to have larger and more persistent real effects in heterogeneous economies when compared to identical-firms economies with similar degrees of nominal and real rigidity.

[3] These results are not typical and crucially depend on assumptions about information structure. For instance, Woodford (2002) assumes that firms pay little attention to aggregate conditions if these signals are noisy. Mankiw and Reis (2002) develop a different model in which information disseminates slowly. In their model prices respond with equal speed to all disturbances.

price adjustment across sectors. I examine two of the model implications discussed above using this calibrated version. The first implication relates to the different nature of the response to aggregate and idiosyncratic shocks observed empirically by BGM. The second implication is the model's ability to generate monetary non-neutrality. I compare the fully calibrated model with equivalent homogeneous economies. I show that the presence of production chains reinforces the heterogeneity in the frequency of price adjustments. In Section IV, I present empirical evidence supporting the third implication of the model – that upstream industries respond faster to aggregate shocks than downstream industries. Using disaggregated data from Manufacturing, I find a significant negative relationship between the position down the production chain and the speed of response to monetary policy and oil price shocks. I conclude in Section V.

II. MODEL

A. Households

The model is a multi-sector version of the workhorse New Keynesian model with monopolistic competition presented in Woodford (2003), Chapter 2, or Walsh (2003), Chapter 5 (among many others). The economy is populated by identical, infinitely lived households of measure one and an infinite number of firms in a J-sector economy. The representative household maximizes a lifetime utility function specified as follows:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\frac{C_{t+\tau}^{1-\sigma}}{1-\sigma} - \chi \frac{L_{t+\tau}^{1+\eta}}{1+\eta} \right]$$

where E_t denotes the expectations operator conditional on information known at time t, C_t denotes the household consumption of a composite consumption good and L_t denotes the household supply of labor. Households own the firms in this economy which means that they receive the profits earned by the firms. Markets are complete and therefore the household's budget constraint may be written as:

$$C_t + E_t \left[\Delta_{t,t+1} B_{t+1} \right] \leq \frac{W_t L_t}{P_t} + \frac{B_t}{P_t} + \sum_{j=1}^{J} \Pi_t^j$$

where B_{t+1} is the stochastic payoff of securities purchased at time t, $\Delta_{t,t+1}$ is the stochastic discount factor, W_t is the wage at time t and Π_t^j denotes total real profits earned by sector j. Wages are assumed to be flexible (I will discuss the implications of relaxing this assumption in subsection A of Section III.

The household's composite consumption good is an aggregator over the variety of all the goods available in the economy:

$$C_t = \prod_{j=1}^{J} \left(\varepsilon^j \right)^{-\varepsilon^j} \left(C_t^j \right)^{\varepsilon^j}$$

where C_t^j denotes the household's consumption of the good produced by sector j and ε_j's are a vector of weights associated with each sector in the consumption basket of the household and they satisfy $\sum_{j=1}^{J} \varepsilon^j = 1$. The Cobb-Douglas functional form assumed is a special case of a CES aggregator with a unit elasticity of substitution. In this specification I follow Bouakez, Cardia, and Ruge-Murcia (2009). The advantage of this specification is that the weights ε^j are equal to the household's sectoral expenditures shares, which can be easily obtained from the sectoral break-up of Personal Consumption Expenditure, reported by the BEA.[4]

Let P_t^j be the price of the good produced by sector j and P_t the aggregate price level in period t, defined as:

$$P_t \equiv \prod_{j=1}^{J} \left(P_t^j\right)^{\varepsilon^j}$$

Then, the cost minimization problem of the household implies that the household's demand for the good produced by sector j, C_t^j, is given by:

$$C_t^j = \varepsilon^j \left(\frac{P_t^j}{P_t}\right)^{-1} C_t \tag{1}$$

Note that the definition above for the aggregate price level also implies that $\sum_{j=1}^{J} P_t^j C_t^j = P_t C_t$.

Once the household has decided the cost minimizing composition of its consumption basket, given the consumption of the aggregate good, it will choose the optimal total consumption expenditure and labor supply. The first-order conditions are standard:

$$\Delta_{t,t+\tau} = \beta^{\tau} \frac{C_{t+\tau}^{-\sigma}}{C_t^{-\sigma}}$$

$$\chi \frac{L_t^{\eta}}{C_t^{-\sigma}} = \frac{W_t}{P_t}$$

Note that the last equation is implied by the assumption about flexible wages.

B. Firms

The J differentiated goods in the economy are produced by one of the J monopolistically competitive sectors. Each sector itself is composed of a continuum of firms of measure one, who produce goods that are imperfect substitutes. These goods are aggregated by a competitive sector

[4] The Cobb-Douglas assumption for the consumption aggregator and the intermediate input aggregator is not essential. All the results will be the same to the first order if a CES aggregator with a non-unity elasticity of substitution is used instead.

into sector j's output. In the interest of brevity the firm level analysis is omitted.[5] Firms are indexed by z. The representative firm in sector j has a production technology as follows:

$$y_t^j(z) = \left(A_t^j L_t^j(z)\right)^{s_j} M_t^j(z)^{1-s_j}$$

where A_t^j is the sector-specific stochastic level of technology. $M_t^j(z)$ is an intermediate input – itself a CES aggregator of all the goods produced in the economy.[6] These goods are combined to form the sector-specific intermediate input according to:

$$M_t^j(z) = \left[\prod_{i=1}^{J} \left(\varsigma_i^j\right)^{\varsigma_i^j} \left(m_{t,i}^j(z)\right)^{-\varsigma_i^j}\right]$$

where $m_{t,i}^j(z)$ is the quantity of input i purchased by firm z in sector j. ς_i^j is the weight of input i in sector j.The weights ς_i^j satisfy $\varsigma_i^j \in [0,1]$ and $\sum_{i=1}^{J} \varsigma_i^j = 1$. Define the price of the intermediate input for industry j as:

$$X_t^j = \left[\prod_{i=1}^{J} \left(P_t^i\right)^{\varsigma_i^j}\right]$$

Given that goods from different sectors are imperfect substitutes in the production function of firms, the demand for each good by other firms depends on its price. Isomorphically to the consumer's problem, cost minimization by firm z in sector j implies that its demand for the goods produced by sector i is determined by:

$$m_{t,i}^j(z) = \varsigma_i^j \left(\frac{P_t^i}{X_t^j}\right)^{-1} M_t^j(z) \tag{2}$$

Given the definition of X_t^j it can be shown that $\sum_{i=1}^{J} P_t^i m_{t,i}^j(z) = X_t^j M_t^j(z)$.

[5] The assumption that each sector is made up of a large number of firms is needed for two reasons. First, for the purposes of calibration, I would like to be able to use the model where J, the number of sectors, is not necessarily very large. If sectors were populated by a single firm, the assumption that sectors take the aggregate prices in the economy as given would become hard to justify. The second reason is that an infinite number of firms existing within each sector allows for deriving sector-specific Phillips curves.

[6] In my notation, I use superscripts to refer to the recipient industry and subscripts to the donor industry. So for instance, $M_t^j(z)$ refers to inputs used by firm z in sector j and $m_{t,i}^j(z)$ refers to inputs produced by sector i and used by firm z in sector j.

1. Market Clearing

Imposing a market clearing condition for each firm and each sector and using demand functions (1) and (2) one can show that:

$$y_t^j(z) = \left(\frac{p_t^j(z)}{P_t^j}\right)^{-\theta} Y_t^j$$

where $Y_t^j = C_t^j + \sum_{i=1}^{J} \int_0^1 m_{t,j}^i(z')dz'$ and θ is the elasticity of substitution between goods within the same sector.

A few points are worth noting; first, following Basu (1995), I have used a "round-about" model of intermediate goods in that all goods could *potentially* be used as an intermediate input and a consumption good. Second, the assumption that the elasticity of substitution between goods is the same for consumption and for production means that the price elasticity of demand for a good does not depend on its use, and therefore there is no distinction, from a producer's point of view, in the two uses for its output and hence there is no price discrimination based on the product's use. Also note that a reasonable choice for θ would imply that $\theta \geq 1$. Furthermore, the elasticity of substitution between goods within a sector is at least as large as that for goods from different sectors, a desirable assumption.

Second, note that whereas all the firms within a sector are identical in the steady state, firms in different sectors are heterogeneous in a number of dimensions: 1) their production functions differ in the intensity with which they use different factors of production, 2) the combination of goods used as material inputs can potentially differ, 3) they differ in the level of their technology. Therefore, in the steady state the relative prices of goods produced by firms within a sector will always be one whereas in general goods from different sectors will have different prices even in the steady state.

Finally, the concept of "production chain" in this paper is related to the difference in the production function of different sectors. In particular, the higher the s_j (the share of labor in production), the lower the dependence on other firms' output in production. I rank industries along the production chain according to their corresponding s_j's. A higher s_j indicates that an industry is earlier in the chain.

Note that there is a close relationship between this definition of a production chain and one in which the chain is defined along a temporal dimension. By the latter I mean a model which assumes upstream firms' output can only be used by more downstream firms with a time lag. Such a model would assume that quantities are fixed and therefore prices adjust to clear the markets in the period following production. In the model I present here, the assumption is that prices may be fixed after the realization of a shock, and therefore, quantities have to adjust in order to clear the market. Thus, the two models are analytically analogous. Yet, the assumption I have chosen allows a comparison of the results presented here with the New Keynesian literature.

2. Firms' Price Setting

Firms face price rigidities of the form described by Calvo (1983). Specifically, in each period a fraction $1-\omega_j$ of the firms in sector j get to adjust their prices whereas the remaining fraction ω_j do not. Those firms who adjust their prices do so to maximize the expected discounted value of current and future profits discounted both by the stochastic discount factor and by the probability of survival of the current price. Therefore, the firm's maximixation problem can be written as:

$$\max_{m^j_{t,i}(z),p^j_t(z),L^j_t(z)} E_t \sum_{\tau=0}^{\tau=\infty} \omega_j^\tau \Delta_{t,t+\tau} \Pi^j_{t+\tau}(z)$$

subject to the production function and the total demand for the good produced by firm z. Period profits of firm z in sector j as a function of the price it sets for its output are defined as:

$$\Pi^j_t(z) = p^j_t(z) y^j_t(z) - W_t L^j_t(z) - X^j_t M^j_t(z)$$

Substituting the demand for a firm's output and optimal choice of inputs, the firm's problem can be written as choosing the optimal price $\tilde{p}^j_t(z)$ to maximize:

$$E_t \sum_{\tau=0}^{\infty} \omega^\tau(j) \Delta_{t,t+\tau} \left[\tilde{p}^j_t(z) \left(\frac{\tilde{p}^j_t(z)}{P^j_{t+\tau}} \right)^{-\theta} - \Psi^j_{t+\tau} \left(\frac{\tilde{p}^j_t(z)}{P^j_{t+\tau}} \right)^{-\theta} \right] Y^j_{t+\tau}$$

where $\Psi^j_{t+\tau}$ is the nominal marginal cost of a firm in sector j. The cost-minimization of the firm implies that $\Psi^j_t = \frac{1}{s_j} \left(\frac{W_t}{A^j_t} \right)^{s_j} \left(X^j_t \right)^{1-s_j} \left(\frac{s_j}{1-s_j} \right)^{1-s_j}$. The interpretation is that the nominal marginal cost is a weighted average of the effective wage and the price of the intermediate good. The higher $1-s_j$ (the further down the production chain an industry is), the higher the dependence on price of the intermediate inputs. An industry "inherits" the stickiness of its suppliers through the dynamics of X^j_t.

C. Monetary Policy and Shocks

The monetary authority acts so as to make nominal GDP follow a random walk with drift in logs. Denote the nominal GDP by $S_t = P_t C_t$. Then,

$$\log S_t = \log S_{t-1} + v_t$$

where

$$v_t = \rho_v v_{t-1} + \varepsilon_{v,t}$$

$\varepsilon_{v,t}$ is a white noise innovation with variance σ_v^2. ρ_v is strictly smaller than 1. The stochastic level of technology in each sector follows a random walk process:

$$\ln(A_t^j) = \ln(A_{t-1}^j) + \varepsilon_{A^j,t}$$

where $\varepsilon_{A^j,t}$ is a sector-specific white noise innovation, uncorrelated across sectors and with variance σ_{Aj}^2. $\varepsilon_{A^j,t}$ and $\varepsilon_{v,t}$ are independent processes.

D. Linearized Steady State

Log-linearizing the optimal pricing decision of a firm around a zero inflation zero output growth steady state, the price setting dynamics imply a Phillips curve relation for each sector j such that:

$$\pi_t^j = \beta E_t \pi_{t+1}^j + \kappa_p^j \left[\varphi_t^j - p_t^j\right] \tag{3}$$

where $\pi_t^j = p_t^j - p_{t-1}^j$ is the change in sector j's (log) price from $t-1$ to t. φ_t^j is the deviation of the nominal marginal cost from its steady state, and $\kappa_p^j = \dfrac{(1-\omega^j\beta)(1-\omega^j)}{\omega^j}$ is a parameter.[7]

III. Calibration

In calibrating the model I begin by choosing some benchmark parameters which will remain fixed throughout all the calibration exercises presented below (Table 1). For consumer's preferences I assume log utility in consumption and a linear disutility of labor $(\sigma = 1, \eta = 0)$. Assuming log utility allows for the existence of a balanced growth path with non-stationary technology shocks in a multi-sector setting (see Ngai and Pissarides (2007)). The assumption on linear labor disutility can be interpreted as indivisible labor with lotteries following Hansen (1985). To calibrate the discount rate I choose an annual interest rate of 3% which corresponds to a monthly value of $\beta = 0.9975$.

I choose $\theta = 8$ for the elasticity of substitution between goods within a sector. This value for θ places it in the middle of the range used in the literature. Nakamura and Steinsson (2008b) use $\theta = 4$. This rather low estimate for θ allows them to have a higher implied intermediate input share in the production function (see the calibration of intermediate input shares below) and thus create greater non-neutrality. Carvalho (2006) uses $\theta = 5$ and $\theta = 11$ as a lower and upper bound, and Golosov and Lucas (2007) use $\theta = 7$. The choice of $\theta = 8$ implies a markup of $\mu = 1.14$, which if interpreted as profits, is a realistic estimate for the US economy. Estimates of markups typically fall in the 10 to 20 percent range, implying values of θ in the 6 to 10 range.[8] Also note

[7] The derivation is standard. See Woodford (2003)

[8] See Rotemberg and Woodford (1993) and Basu and Fernald (1997).

that $\theta = 8$ is larger than the elasticity of substitution between goods from different sectors (assumed to be 1), which is a reasonable assumption.

To calibrate the characteristics of monetary policy shocks, I estimate an $I(1)$ model for the quarterly US nominal GDP during the period 1948 to 2008. The estimate for the standard deviation of nominal GDP growth corresponds to quarterly values for $\sigma_\upsilon = 0.004$ (monthly $\sigma_\upsilon = 0.0025$) and $\rho_\upsilon = 0.50$, which are in line with estimates in the literature. I choose the variance of the sector-specific productivity shock $\sigma_A = 0.01$ to match the median estimate of the unconditional (monthly) variance of the idiosyncratic shock found in the BGM FAVAR exercise across the PPI prices.

In the remainder of this section, I will go through four calibration exercises. To make the intuition clear, I first calibrate the model to an "extreme" two-sector production chain, where one good is solely used as an intermediate input and the other entirely as a consumption good. In the subsequent three calibration exercises, I gradually build a 6-sector version of the US economy: In the second exercise, I calibrate the production share of the intermediate goods in each sector using the BEA's Input-Output (IO) Use table but assume that sectors are homogenous along all other dimensions. Next, I add heterogeneity in the parameter describing the Calvo frequency of price adjustment across sectors, and finally, I allow for varying intensity with which a good is used for consumption vs. as an input for production, again using the IO Use table. In terms of the notation introduced earlier, these intensities correspond to calibrating the ς_i^j and ε^j shares.

At the end of this section, I present a version of the model in which the production technologies are characterized by decreasing returns to scale.

A. A Two-Sector Example

Here, I develop a special example of the economy described above. This economy is composed of two sectors. Sector 1 only uses labor in its production function $(s_1 = 1, Y_t^1 = A_t^1 L_t)$, and sector 2 only uses material inputs, which are solely composed of sector 1 goods $(s_2 = 0,\ \varsigma_1^2 = 1, Y_t^2 = A_t^2 Y_t^1)$. Finally, the consumption basket is entirely composed of good 2 $(\varepsilon^2 = 1, C_t = Y_t^2)$. The log-linearized model can be represented by two Phillips curves, a wage setting equation, the stochastic path of nominal aggregates and the aggregate production equation.

$$
\begin{gathered}
\pi_t^1 = \beta E_t \pi_{t+1}^1 + \kappa_p^1 \left[w_t - p_t^1 - a_t^1 \right] \\
\pi_t^2 = \beta E_t \pi_{t+1}^2 + \kappa_p^2 \left[p_t^1 - p_t^2 - a_t^2 \right] \\
w_t - p_t^2 = \sigma c_t + \eta l_t \\
c_t + p_t^2 - \left(c_{t-1} + p_{t-1}^2 \right) = \nu_t \\
c_t = a_t^1 + a_t^2 + l_t
\end{gathered}
$$

Figure 1 shows the response of prices for the two sectors to a shock to monetary policy (Panel (A)) and to their own idiosyncratic TFP shock (Panel (B)). Sector 2 responds more slowly to a monetary policy shock because its marginal cost is the slow-moving price of sector 1 output. On the other hand, the responses of each sector to a shock in its sector-specific technology (a_t^i) are indistinguishable. This is not surprising given that the two sectors are identical except for their position in the production chain.

Note that the relative speed of response to an aggregate shock remains the same regardless of the assumption about wage rigidity. To see this more clearly note that $Y_t^1 = A_t^1 L_t$ and $Y_t^2 = A_t^2 Y_t^1$. Therefore, even if sector 2 's price is flexible compared to wages, since the marginal cost in sector 2 follows the price of sector 1 output, the prices in sector 2 inherit the sluggishness in the response of sector 1 through the marginal cost movements. Thus, Sector 2 would be slower in responding to an aggregate shock. This intuition holds in all the exercises presented below; and although wage rigidity affects the overall amount of monetary non-neutrality created in response to a monetary policy shock, it does not affect the order in which sectors respond to aggregate shocks. Thus, in the interest of brevity, I only present the results under the assumption of flexible wages in the main text, but the same exercises are repeated for a model with staggered wage setting *à-la* Erceg, Henderson, and Levin (2000) in Appendix A.

B. The Multi-Sector Model

I calibrate the multi-sector model to a 6-sector version of the US economy. The sectors are Agriculture, Mining, Utilities, Construction, Manufacturing and Services. These sectors correspond to the most aggregated industry classification in the BEA IO table.[9] I start by calibrating the sector shares to the US IO Use matrix. Given the Cobb-Douglas form assumed for the production function, the input share in production will be proportional to expenditure share $\left(1 - s_j = \mu \frac{M^j X^j}{P^j Y^j}\right)$. The expenditure shares are readily available from the IO Use table. The corresponding labor shares for each sector are reported in Table 2. The final column in Table 2 shows the estimates of s for some of the sectors included in Bouakez, Cardia, and Ruge-Murcia (2009), who estimate the parameters of a similar multi-sector model.[10]

[9] I exclude Government and some other categories of services including Trade, Finance and Health Care. The latter are excluded for the lack of data on the frequency of adjustment in prices, which will be used to calibrate the Calvo adjustment parameters of each sector in the full calibration in case 3. The largest two omissions are Financial services and Business services, which together amount to 40% of total value added.

[10] Bouakez, Cardia, and Ruge-Murcia (2009) assume the following production function for the firms in sector $j : y_t^j = (z_t^j n_t^j)^{\nu_j} (k_t^j)^{\alpha_j} (H_t^j)^{\gamma_j}$, where z_t^j is a sector-specific productivity shock, k_t^j is capital, H_t^j is material inputs, and $\nu_j + \alpha_j + \gamma_j = 1$. They estimate the production function parameters using the yearly data on nominal expenditures on capital, labor and material inputs for each sector collected by Dale Jorgenson for the period 1958 to 1996.

Case 1: Heterogeneity in s_i

In this exercise the only source of heterogeneity between the sectors is the intensity with which they use intermediate inputs vs. labor. Therefore, only the s column in Table 2 is relevant. I calibrate the (monthly) Calvo price stickiness in all sectors with $\omega_i = 0.85$, which is close to the corresponding median frequency of price adjustment reported by Nakamura and Steinsson (2008a) for intermediate goods. This value implies a duration of 7.6 months which is close to the slightly larger than average duration of price rigidity reported by Carvalho (2006), 6.6 months, using data from Bils and Klenow (2005). The response of this economy to a shock to the nominal GDP process v_t is shown in panels (a) to (c) of Figure 2. As would be predicted by the model, Utilities, the sector earliest in the chain (characterized by the largest labor share), responds first whereas Manufacturing, the latest industry in the chain, is the slowest.

The differences in the speed of response mean that the existence of a production chain creates short-run relative price effects. This non-neutrality caused by monetary policy can be measured in several ways. I look at the maximum relative price across all the sectors at all horizons in response to a monetary policy shock in the first row of Table 3. Note that without any heterogeneity in labor shares this metric would be equal to zero. I also report the maximum standard deviation between prices at any horizon t (row 2). This standard deviation is another way of measuring the extent to which relative prices deviate from 1 at each time. Thus, this measure would also be equal to zero in the absence of heterogeneity in sectoral characteristics. In other words, these two measures would not be useful in measuring monetary non-neutrality in a one-sector model.

In order to compare the non-neutrality of the multi-sector economy with an equivalent single-sector economy, I report two measures of non-neutrality for the overall economy. First, I report the conditional variance of consumption's response to a monetary policy shock. An alternative measure, following Midrigan (2007) and Nakamura and Steinsson (2008b), which I also report, is the variance of real value-added output when the model is simulated with purely nominal aggregate shocks, respectively in rows 3 and 4 of Table 3.

The relative price effects are not uniform across sectors either. Panel (A) of Figure 6 shows the deviations of relative sectoral prices from their steady state levels in response to a monetary policy shock. This is captured by plotting sectoral prices relative to that of Utilities. The figure shows that the relative prices are not large, around 7%. Also, it is intuitive that the largest relative price effect is between the Manufacturing and Utilities sectors with the largest difference in their intermediate input shares.

I now look at price responses to technology shocks. The sectoral price responses to a productivity shock in their own sector are demonstrated in Panel (B) of Figure 2. The non-stationary productivity shocks cause permanent relative price effects, and the larger the labor share of a sector, the larger the effect of a one standard deviation shock on its final price. This property naturally follows the assumption that technology is labor-augmenting.

Panel (C) of Figure 2 shows the response of sectoral prices to a common productivity shock. The aggregate productivity shock can be thought of as a common component to technology shocks across different sectors. The response to an aggregate productivity shock is nearly identical to the response of sectoral prices to a monetary policy shock. This result justifies the BGM classification of shocks into aggregate vs. idiosyncratic regardless of whether they are supply-side or demand-side shocks.

That an aggregate productivity shock leaves the relative prices unaffected in the long-run is because increases in productivity are "shared" among sectors through uses of intermediate inputs. Given the Cobb-Douglas structure of the production functions across sectors, it can be shown that an aggregate technology shock leaves relative prices unchanged in the long-run (see Appendix B).

Case 2: Heterogeneity in s_i and ω_i

In this exercise I add heterogeneity in the Calvo price adjustment parameter across sectors in addition to varying s_i. The ω_i are matched to the PPI-based frequency of price adjustment reported by Nakamura and Steinsson (2008a). I match their products to the larger NAICS categories included in the definition of industries in the IO Use table, provided by the BEA. The frequency of adjustment for each sector is the median frequency of adjustment of all the categories within that sector. The calibrated values are reported in Table 2. In this section's calibration only columns corresponding to s and ω are relevant.

The responses to the shocks discussed in the previous calibration exercise are reproduced for the new calibration and are presented in Figure 3. Note that the heterogeneity in the response to a monetary policy shock substantially increases compared to Case (1). The real effects of monetary policy are summarized in Table 3. Compared to the previous case, where ω_i values were constant across sectors, the real effect of monetary policy has also increased substantially.

Furthermore, how fast an industry responds to an aggregate shock is determined by a combination of the size of ω_i and the position of the sector in the chain. Utilities is still the fastest sector to respond but Agriculture and Manufacturing are no longer the slowest industries. Note that despite having the highest frequency of price adjustment, agricultural prices respond more slowly than either Utilities or Mining because Agriculture has a high share of intermediate inputs, which affect its marginal cost.

In the same way, the relative price effects are a affected by differences in intermediate input shares and by differences in ω_i. Panel (B) of Figure 6 shows the largest deviation of relative prices compared to the steady state is now between Utilities and Services, mainly due to the sticky nature of Services prices. The figure shows that the relative price effect is large, reaching around 45%.

The response to sector-specific productivity shocks are shown in Panel (B). First note that the long-run response to these shocks is not different from those in the previous case. This is expected because the only difference between the Case (1) and Case (2) calibrations is the heterogeneity in ω_i which should not affect the long-run response. Also note that the responses cross. The reason is that the short-run response is driven by the heterogeneity in ω_i whereas the long-run responses reflect the heterogeneity in s_i. To the extent that ω_i and s_i are not perfectly correlated, the short-term and long-term ordering of prices may differ.

Case 3: Heterogeneity in ε^j and ς_i^j

Up to now I have assumed that all sectors are used with equal weights in the consumption and intermediate good baskets. Empirically, this is unrealistic. In this section, I calibrate the ε^j and ς_i^j weights to the IO Use matrix. The Cobb-Douglas form assumed for consumption and intermediate good aggregator would imply that ε^j is the expenditure share of good C^j in total consumption expenditure. Therefore, ε^j are readily available by taking each sector's share in the "Personal Consumption Expenditure" column of the IO Use matrix.

The ς_i^j denotes the share of sector i in the intermediate input of sector j. So potentially, we could have $n \times n$ different values. In the interest of tractability I will make the simplifying assumption that $\varsigma_i^j = \varsigma_i^k = \varsigma_i$ for all i, j and k. This means that the composition of the intermediate good is the same for all sectors (across the recipient sectors), but in the composition of the intermediate input, different sector outputs are used with different intensities ($\varsigma_i \neq \varsigma_j$). I compute ς_i^j as the expenditure on intermediate inputs purchased from sector i as a share of total intermediate input expenditure for sector j. I then compute $\varsigma_i = \sum_j \lambda^j \varsigma_i^j$, where λ^j is the weight of sector j in the economy.

The calibrated values for ε^j and ς_i are shown in Table 2. Services form a large share of consumption whereas Manufacturing is the largest share of the intermediate good. Using the new calibrated ε^j and ς_i, and keeping s_i and ω_i as before, I again simulate the model subject to the three different shocks discussed above. Figure 4 shows the result. The relative speed of response has not changed compared to the previous case.[11] However, the overall amount of monetary non-neutrality is affected, as this economy puts a higher weight on two of the stickiest sectors of the economy: Services (because of a low Calvo price adjustment frequency) and Manufacturing (a sector at the end of the production chain). Compare the cumulative response of the GDP to a monetary shock in the fully calibrated model (last column) with a perfectly homogeneous economy, in which $s = 0.38$ and $\omega = 0.62$ (Note that these values are equal to the weighted average of s and ω in the heterogeneous economy). Table 3 shows that the realistically calibrated heterogenous model creates around five times more rigidity compared to the "equivalent" homogeneous economy (0.38 c.f. 0.07).

[11] My conjecture is that under extreme assumptions about the composition of intermediate inputs, this result may be reversed.

C. Discussion of results

Creating sufficient non-neutrality has been one of the challenges of monetary models in a DSGE context. The New Keynesian models create notoriously little rigidity for reasonable levels of micro rigidities assumed. However, through previous research (Carvalho (2006), Nakamura and Steinsson (2008b) and many others), we have learned that richer, more realistic models of an economy will go a long way in increasing the real effects caused by nominal shocks. The model presented in this paper includes some of the ingredients found in previous papers as important – existence of intermediate inputs and heterogeneity in the frequency of price adjustment – and adds new ones: heterogeneity in the production functions across sectors and the possibility of decreasing returns to scale. A realistic calibration of the model to a six-sector version of the US economy shows that these two assumptions are featured in the data.

Nakamura and Steinsson (2008b) report the variance of HP-filtered log US real GDP for the period 1988 to 2006 to be 0.81×10^{-4}. Table 3 shows that the benchmark homogeneous economy model (one representative sector), with intermediate inputs equal to the average in the economy, produces less than a tenth of the variance in output observed in the data. The most realistic calibration of the model under constant returns to scale assumptions is presented in Case (3), where sectors differ in the relative intensity with which they use factors of production, their relative sizes in consumption and intermediate input baskets and the frequency of price adjustment. This model implies a volatility for real GDP which is about 45% of the fluctuations in the real GDP in the data. Finally, in a model with DRS this share rises to about 55%.

To conclude, the exercises above demonstrate that departure from the simplified model of a one-sector homogeneous economy is an important step in capturing the quantitative effects of nominal shocks on the output in the short-run. Furthermore, this class of multi-sector models are important to understand the short-run relative price effects of monetary policy and the optimal monetary policy response as discussed, for instance, in Aoki (2001).

IV. Empirical Evidence

The relevance of the production chain as a mechanism for amplifying the micro-level nominal rigidities in the economy is consistent with the findings of a few papers on the frequency of price adjustment. BGM report much faster responses for the PPI to monetary policy shocks compared to the CPI. Nakamura and Steinsson (2008a) report that the frequency of price change is strongly related to the stage of processing. Although this fact could be evidence for different intrinsic factors of price stickiness, such as higher variance of idiosyncratic shocks at the crude material level or lower costs of price change, it is also consistent with the lower speed of response to shocks as predicted in the production chain model. In this section, I will explore this issue.

One implication of the model presented above was that *ceteris paribus*, upstream industries respond faster to aggregate shocks compared to downstream industries. I test this prediction against the data by considering the response of prices to two types of aggregate shocks: a monetary policy shock and an oil supply shock. I regress the cumulative response of disaggregated prices of around 150 industries in Manufacturing to these shocks on a measure of their position in the production chain, which I will define below, as well as other explanatory factors. I find a significant and negative relationship between the position in the chain and the speed of response at different horizons.

In this section I will present the empirical evidence. First, I will discuss the identification of the shocks and the implied impulse responses of sectoral prices. I will then present the reduced form regressions.

A. Identification of Shocks and Impulse Responses

I use two measures of identified monetary policy shocks. The first is the Romer and Romer (2004) measure of monetary policy shocks, which uses a narrative approach based on the detailed examination of the Federal Reserve's meeting minutes. The second is monetary policy shocks as identified by the FAVAR method in BGM. A summary of the assumptions for this method is included in Appendix C.1. In an isomorphic fashion I use two estimates for oil supply shocks, both due to Lutz Kilian. The first approach is similar to the Romer and Romer (2004) analysis in that oil supply shocks are identified by examining historical events and their effects on oil prices. The second is a VAR approach based on co-movements of changes in oil production, real oil prices and global economic activity Kilian (2009). I embed this VAR approach into a factor-augmented framework, similar to the one used by BGM to identify monetary policy shocks. A more detailed description of this identification scheme is also included in Appendix C.2.

Under the narrative approach, in order to find the impulse response of each price series to the identified shocks I proceed as follows. The response to the two historical measures of monetary policy and oil price shocks can be computed directly. In particular, I run the following regressions:

$$\Delta p_{it} = a_{i0}^{MP} + \sum_{k=1}^{11} a_{ik}^{MP} D_{kt} + \sum_{j=1}^{24} b_{ij}^{MP} \Delta p_{i,t-j} + \sum_{j=1}^{48} c_{ij}^{MP} S_{t-j}^{MP} + e_{it}^{MP}$$

$$\Delta p_{it} = a_{i0}^{O} + \sum_{k=1}^{11} a_{ik}^{O} D_{kt} + \sum_{j=1}^{24} b_{ij}^{O} \Delta p_{i,t-j} + \sum_{j=1}^{64} c_{ij}^{O} S_{t-j}^{O} + e_{it}^{MP}$$

where p_{it} is log of individual PPI price series described in the previous section and indexed by i, D_{kt} are monthly dummies, $\Delta p_{i,t-j}$ are lags of inflation for the price series being analyzed and S_{t-j}^{MP} and S_{t-j}^{O} are the measures of monetary policy and oil price shocks, respectively. In the two regressions above superscripts MP and O refer to monetary policy and oil regressions, respectively.

In the monetary policy regression I use exactly the same number of lags as Romer and Romer (2004). They use 24 lags of monthly inflation series, and 48 lags of the shock series to analyze the effect of their measure of monetary policy shocks on the price index for finished goods. The regression is performed on monthly data and the regression dates are 1976:1 to 1996:12. For the oil supply shock, I try different lag specifications.

In analyzing the inflation response Kilian (2008) uses four lags of the inflation series and eight lags of oil price, both on a quarterly basis. Given that the oil shock and price series are both available in monthly frequency, I use the monthly data in the oil supply shock regression to be consistent with the monetary policy shock regression. I use the same number of lags for the inflation series (24 months), but longer lags for the oil price shock to capture the notion that an oil price shock might take longer to affect production and prices. The results presented in the paper are robust to changes in these horizons and use of quarterly data as in Kilian (2008). The regression uses data from 1976:1 to 2004:9. The impulse response of prices to monetary (oil) shocks can be directly computed using b_{ij}^{MP} and c_{ij}^{MP} (b_{ij}^{O} and c_{ij}^{O}) coefficients.

To find the impulse response of prices to monetary and oil price shocks using a VAR, I follow closely the FAVAR approach in BGM. Briefly, this amounts to extracting a number of latent factors from a large data set, including all the sectoral prices and major series describing the state of the US economy. In the case of monetary policy shocks, the federal funds (FF) rate is added to the latent factors. The VAR is composed of the latent factors as well as the FF rate with a recursive identification assumption which imposes that the FF rate can respond to all factors within a month, but not vice-versa. Monetary policy shocks are identified this way, and the corresponding impulse responses for each price series can be computed. The approach is described in more detail in Appendix C.1.

A similar approach is used for identifying oil price shocks. Following Kilian (2009) I impose that the monthly change in the global oil production, a measure of global real economic activity and real oil prices are the three observable factors. The identification assumption, as discussed in Kilian (2009), is that production does not respond within a month to changes in real economic activity and real oil prices, and economic activity cannot respond within the same month to changes in real oil prices whereas real oil prices can respond to shocks to all the factors. The identification scheme is discussed in more detail in Appendix C.2.

Finally, I need to construct a measure for the position of an industry in the production chain. I define the position of sector i in the production chain as:

$$pos_i = \frac{\text{total final use of } y_i}{y_i}$$

i.e. the position of the industry *i* in the chain is determined by how intensively it is used as a final good as a share of that industry's total output. The higher this ratio, the further downstream is the corresponding industry.

B. Data

The data for the FAVARs are exactly the same as those used in the BGM exercise. This is a balanced panel of 653 monthly series for the period running from 1976:1 to 2005:6. The choice of the initial date reflects the fact that a significant number of the disaggregated PPIs start in 1976:1. All data have been transformed to induce stationarity. The original and transformed data are posted by the authors on the World Wide Web.[12]

To find the impulse response of prices to monetary policy shocks identified by Romer and Romer (2004), I directly take their measure for monetary policy which is also available on the Web.[13] This measure documents monthly shocks to monetary policy from 1969:1 to 1996:12. Therefore, the regressions based on this measure of monetary policy use monthly data from 1976:1 to 1996:12. I append 24 months of zero inflation to the disaggregated price data (starting from 1974:2) in order to avoid throwing away the first 24 months of price data needed for the AR structure of the regression.

To identify oil supply shocks in the FAVAR framework, as well as the panel describing the economy, I need the monthly index of real activity which is available from Lutz Kilian's website.[14] The oil production and real oil price data are also readily available from the Department of Energy's Energy Information Administration. The three series required to repeat the Kilian exercise are available from 1974:1 to 2006:10, and therefore, the entire BGM panel can be used in this framework.[15]

Finally, for the identification of oil supply shocks using the historical measure, I use the monthly historical oil supply shocks identified by Kilian (2008) based on episodes of political turmoil in the Middle East. This data is available from 1973:1 to 2004:9. Therefore, the impulse responses based on this measure are calculated using monthly data on prices and oil supply shocks from 1976:1 to 2004:9. All sectoral inflation between 1973 and 1976 are assumed to be zero, but this will only affect the estimates using the first few months of data.

[12] http://www2.gsb.columbia.edu/faculty/mgiannoni/research.html

[13] http://elsa.berkeley.edu/~dromer/

[14] http://www-personal.umich.edu/~lkilian/rea.txt

[15] Kilian starts his series from January 1973 because he uses the Barsky and Kilian (2001) estimates of oil prices, which begin earlier than the series published by the Energy department, which starts in January 1974. Given that the price data used in the FAVAR start in 1975, I do not use this extension.

C. Regressions

As a first pass at the data, I use the Bureau of Labor Statistics classification of PPI commodity data by their stage of processing. This classification covers 1893 commodity categories classified into three stages of processing: “Crude materials for further processing”, “Intermediate materials, supplies and components” and “Finished goods.”

Figure 7 to Figure 10 show the impulse response of price indices for each of these three broad categories to the four aggregate shocks discussed above. For the two monetary policy shocks, the relative speed of response of the different price categories strongly support the prediction of the model. The response of the final goods is much slower than that of the intermediate goods, and the crude materials are the fastest to respond. The response of prices to oil shocks, particularly when identified in the FAVAR, also suggests the same order in the speed of response. However, it seems that crude prices are much more volatile and far fewer lags are needed to estimate their response to oil price shocks.

For more conclusive evidence, I now use the responses of the 153 industries used by BGM in their sectoral regressions. I regress the response of disaggregated prices to shocks above at different horizons on pos_i, defined above. The model would predict a negative relationship between the speed of response of an industry to an aggregate shock and the measure pos_i. Under the assumption of neutrality of money, all prices should respond by the same amount to a monetary policy shock in the long-run. Therefore, the magnitude of the response of a price series at any time horizon is a valid measure of its speed of response.[16]

On the other hand, oil prices can have also long-run level effects. Thus, the magnitude of response cannot be used as an indicator of the speed of response. To control for this level effect, I either control for the long-run effect or control for the level of energy use. I construct an index for the energy use, which is the total expenditure on energy as a share of total expenditure on intermediate inputs for each industry. Controlling for this index of energy use should allow a separation of the long-run level effect of oil price shocks on sectoral prices from the short-run transition effects. Therefore, I expect the coefficient on the index of energy use to be negative.

Furthermore, BGM find that other factors, such as the standard deviation of the sector-specific shocks or the degree of competition in an industry, can affect the dispersion in the response to monetary policy shocks. Therefore, I also include those variables in my regressions. In particular, I will use the following specifications for the cross-industry price responses:

[16]This assumption would be invalid if the speed of response changes along the IRF. In other words, if there is a lot of change in the ordering of prices, the magnitude of response is not a good proxy for its speed. The correlation of the speed of response has to be constant along the IRF. The correlation of the ordering of prices between six, nine and twelve month horizons shows a positive, albeit not very large, correlation. Also, I avoid using the estimated responses at longer horizons as these are less precisely estimated compared to the estimates at earlier horizons.

$$IR_{i,h}^{MP} = \alpha + \beta_1 POS_i + \beta_2 s.d.(x_i) + \beta_3 profit + \beta_4 \rho(x_i) + \varepsilon_i \quad (4)$$
$$IR_{i,h}^{O} = \alpha + \beta_1 POS_i + \beta_2 s.d.(x_i) + \beta_3 profit + \beta_4 \rho(x_i) + \beta_5 energy + \varepsilon_i \quad (5)$$
$$IR_{i,h}^{O} - IR_{i,m}^{O} = \alpha + \beta_1 POS_i + \beta_2 s.d.(x_i) + \beta_3 profit + \beta_4 \rho(x_i) + \varepsilon_i \quad (6)$$

where $IR_{i,h}^{MP}$ ($IR_{i,h}^{O}$) is the log of price level in industry i, h periods after an expansionary monetary policy shock (positive oil price shock); pos_i is the share of final use of industry i output; $s.d.(x_i)$ is the standard deviation of the inflation series, $\rho(x_i)$ is the persistence of the inflation series, $profit$ is the level of profits as a share of output – a measure of competitiveness in industry i which BGM find significant – and finally, $energy$ is the total energy input as a share of total inputs.

The specification is similar to that in the cross-sectional analysis by BGM. I control for all factors that they find significant in explaining cross-sectional dispersion in response to aggregate shocks and argue the position in the chain still has some explanatory power. However, there is one small difference. In BGM, $s.d.(x_i)$ and $\rho(x_i)$ are replaced by $s.d.(e_i)$ and $\rho(e_i)$, where e_i is the VAR error term. These estimates, though consistent, suffer from generated regressor bias, and therefore, I need to correct the standard errors. I use $s.d.(x_i)$ and $\rho(x_i)$ (properties of the inflation series) as instruments for $s.d.(e_i)$ and $\rho(e_i)$. Table 6 shows that these are indeed strong instruments, particularly in the case of $s.d.(x_i)$. Note that I use $IR_{i,h}^{O}$ to $IR_{i,m}^{O}$ as the dependent variable in regression ((6)) as opposed to using $IR_{i,h}^{O}$ as the dependent variable and controlling for $IR_{i,m}^{O}$ on the right-hand side. Again, this is to avoid the generated regressor problem as $IR_{i,m}^{O}$ are also estimated in the VAR.

Given the specification above the model suggests that β_1 is negative. BGM find a positive estimate for β_2 and a negative estimate for β_3, both statistically significant. A positive β_2, although not predicted by the pricing model presented in this paper, could suggest some form of menu-cost pricing: firms with highly volatile idiosyncratic shocks need to adjust their prices often, and hence, they will also respond faster to aggregate shocks. A negative β_3 suggests that in those sectors with higher profit levels (associated with less competitive sectors) prices respond more slowly. Finally, I expect β_5 in the first oil regression to be positive.

Table 7 and Table 8 show the regression results. First, note that the estimates of the effect of the position in the chain on the speed of chain (*pos*) is negative and significant in almost all the regressions presented. Furthermore, the estimates are quite close despite the fact that the dependent variables across different regressions represent responses to different shocks (or at least the same shocks identified with different strategies).

Looking at Table 7 the estimates for *pos* can be interpreted as the effect of moving an industry from the "end" of production chain to the "beginning" of chain. These estimates say that an industry would respond between 20 to 40 percent faster if it were moved from the end of the chain to the beginning. This effect is economically significant. Of course, as found in BGM, the effect of one unit larger standard deviation of idiosyncratic shocks is several orders of magnitude larger.

Table 8 confirms the same intuition for response to oil supply shocks. In the first two regressions of each panel I use IR_9^O to IR_{12}^O as a measure of the speed of response of prices between months nine and twelve. As explained earlier, the purpose of this choice of variable is twofold. First, I need to control for the long-run level response to an oil price shock. Second, to avoid a generated regressor problem, I use the difference in the 9-month and 12-month responses as my preferred measure of independent variable. In regressions (3) to (4) instead I use the share of energy use in total intermediate inputs to control for the long-run effects.

Here, again the estimates of the coefficient on *pos* are all negative and mostly significant, albeit slightly smaller than the estimates obtained from the monetary policy responses. The estimates of the *energy* coefficient are quite small in the regressions based on the FAVAR impulse responses but are significant and have the correct sign in the historical-based regression. Overall, the coefficient on *energy* is less robust in alternative specifications of the horizon at which the regression is performed compared to controlling for the long-run response. This might be an indication that the *energy* index formed this way does not fully capture the extent of the energy use or the relationship between the speed of response and the degree of energy use is not correctly specified.

Overall, these results lend support to the hypothesis that the position of an industry in the chain can affect the speed of its price response to aggregate shocks through the dependence of the industry's marginal cost on other prices in the economy.

V. CONCLUSIONS

Several recent papers have argued that there is significant heterogeneity in the behavior of prices across different sectors, and a literature has emerged to identify the sources of this heterogeneity. This paper belongs to this strand of research. In particular, this paper asks whether the existence of a production chain structure in the economy can be an important source of heterogeneity in the response of sectoral prices to shocks.

I present a multi-sector New Keynesian model incorporating production chains. Different sectors in the economy use inputs with varying intensity. Industries that mainly use labor as their input to production are classified as upstream whereas those heavily dependent on intermediate inputs from other sectors for their production are classified as downstream industries. I discuss three implications of this model.

First, the input-output linkages in production can create heterogeneity in the response of sectoral prices to aggregate shocks. The model suggests that if there are small nominal rigidities, industries at the end of the chain "inherit" these rigidities from their suppliers and hence respond more slowly to aggregate shocks. In response to idiosyncratic shocks, on the other hand, the first-order effect of a change in productivity comes into effect immediately, and thus, is reflected in the price regardless of the position in the chain. The implications of this model seem consistent with the stylized fact (documented in BGM) that prices only respond slowly to aggregate shocks whereas the response to sector-specific shocks is fast.

Second, in a realistic calibration of this multi-sector model to the US data, heterogeneity in the frequency of price adjustments can reinforce the heterogeneity in response to aggregate shocks associated with the position in the chain, generating large rigidities in response to monetary shocks. The introduction of intermediate goods increases non-neutrality as pointed out by Nakamura and Steinsson (2008b) and others. Furthermore, Carvalho (2006) shows that heterogeneity in sectoral frequency of price adjustment also increases rigidities. Using data on the sectoral frequency of price adjustment, I show that differences across sectors in the intensity of intermediate input use reinforces the heterogeneity in sectoral price adjustment frequencies. So, an equivalent "average" economy might be underestimating the amount of non-neutrality quite substantially.

Finally, the model implies that upstream industries would respond faster to aggregate shocks compared to downstream industries. I test this prediction against the data by looking at the response of 150 Manufacturing industries to two types of aggregate shocks: a monetary policy shock and an oil supply shock. I find a significant and negative relationship between the position in the chain and the speed of response at different horizons. This evidence supports the view that the existence of production chains is an important mechanism for the propagation of aggregate shocks and helps explain the heterogeneity across sectors in response to these shocks.

APPENDIX A. RESULTS IN THE PRESENCE OF WAGE RIGIDITY

Here, I have reproduced Figure 2 to Figure 4 in the presence of wage rigidity. In modelling wage rigidity I follow Erceg, Henderson, and Levin (2000) staggered wages setup. The assumptions about households' problem are altered slightly to allow for this setup. In particular, I assume a continuum of monopolistically competitive households each of which supplies a differentiated labor service to the production sector. Under these assumptions, Erceg, Henderson, and Levin (2000) show that a wage setting equation analogous to the price setting Phillips curve can be derived:

$$\omega_t = \beta E_t \omega_{t+1} + \kappa_\omega \left[mrs_t - \zeta_t \right]$$

where $\omega_t = w_t - w_{t-1}$ is the wage inflation at time t, $\kappa_\omega = \dfrac{(1-\varphi^w\beta)(1-\varphi^w)}{\varphi^w}$ is a constant related to the stickiness of wages (φ^w), and ζ_t is the real wage. I calibrate the probability of the nominal wage stickiness such that $\varphi^w = 0.85$. This calibration implies that wages are more rigid than all of the sectoral prices.

The important point to note is that the ordering of sectoral responses does not change in the presence of wage rigidity. This is due to the intuition provided in the two-sector case. Industries further down the change inherit the stickiness of earlier ones regardless of the source (wage or price stickiness).

APPENDIX B. LONG-RUN RESPONSE OF PRICES TO AN AGGREGATE TECHNOLOGY SHOCK

First, I prove that $x^{LR} = -a$, where x^{LR} is the long-run response of the price of intermediate input, and a is the size of aggregate technology shock, where the term "aggregate technology shock" implies $a_i = a_j = a, \forall i$. The proof is by contradiction. Let $x^{LR} = -b$. Then, for each sector i the long-run price response implied is:

$$\begin{aligned} p_i^{LR} &= s_j(w - a_j) + (1-s_j)x^{LR} \\ &= -s_j a - (1-s_j)b \end{aligned}$$

The second line follows because $\eta = 0$ implies perfectly elastic labour supply, and therefore, $w = 0$. The definition of x implies:

$$\begin{aligned} x^{LR} &= \sum \varsigma_i p_i^{LR} = -b + \sum \varsigma_i s_i (b-a) \\ &= -b \end{aligned}$$

The second line follows from our assumption about the long-run response of x. This must be true for any vector s and ς, which implies $b = a$ and $x^{LR} = -a$. It immediately follows that:

$$\begin{aligned} p_i^{LR} &= s_j(w - a_j) + (1 - s_j)x^{LR} \\ &= -a, \forall i \end{aligned}$$

Appendix C. Monetary Policy and Oil Price Shock FAVAR

The empirical framework is based on the factor-augmented vector auto-regression model (FAVAR) described in BGM and originally used by to Bernanke, Boivin, and Eliasz (2005) (BBE). The main feature is to extract a few key variables, or "latent factors", from a large set of economic variables in order to summarize the movements of the macroeconomy. This strategy is particularly useful for eliminating the identification problems associated with small size VARs. As largely documented in this literature, a VAR specification based on an information set smaller than that of the policy maker will be potentially misspecified. The FAVAR framework addresses this problem by using a large information set from which factors are extracted.

Furthermore, the FAVAR model allows for decomposing fluctuations in all variables into common and idiosyncratic movements. BGM use this feature to establish their stylized facts about the responses of disaggregated prices to aggregate vs. idiosyncratic shocks. As the methodology for factor decomposition and identification of monetary policy shocks is based on BGM, I only provide a brief description of the assumptions here and refer the interested reader to BGM for more details.

C.1. Identifying Monetary Policy Shocks

The assumption is that the economy is affected by a vector of factors, C_t, which are common to all variables entering the data set. To estimate this vector of common components I follow BGM. I impose that one of these factors is the FF rate as we are interested in identifying monetary policy shocks. The rest of the common dynamics are captured by a $K \times 1$ vector of unobserved factors F_t. These unobserved factors may reflect general economic conditions such as "economic activity" or the level of "productivity," which are captured by a wide range of economic variables. The dynamics of C_t are given by:

$$C_t = \Phi(L)C_{t-1} + v_t \tag{7}$$

where

$$C_t = \begin{bmatrix} F_t \\ R_t \end{bmatrix}$$

and $\Phi(L)$ is a lag polynomial. The error term v_t is i.i.d. with mean zero and covariance matrix Q. Equation ((7)) defines a VAR in C_t except that the F_t are unobservable. I follow a similar strategy to BGM to extract these factors in a two-step principal components approach. In the first step principal components are extracted from the entire data set. In the second step the FF rate is appended to the estimated factors so that the VAR described in ((7)) can be estimated.

To identify a monetary policy shock, again, I follow the strategy described in BGM. Specifically, I assume that the FF rate may respond to contemporaneous fluctuations in estimated factors but that none of the latent factors of the economy can respond within a month to unanticipated changes in monetary policy. This is the FAVAR version of the standard VAR identification schemes of monetary policy shocks. Note that this identification assumption implies that all the variables (including price series) are allowed to respond to monetary policy immediately insofar as this is a response only to the monetary policy shock directly and not through changes in other latent factors. In all of the simulations presented here, I extract five latent factors. The results are similar with seven, nine, and ten extracted factors.

C.2. Identifying Oil Price Shocks

To identify oil price shocks in VAR, I use the identification scheme proposed by Kilian (2009) and embed it in the factor augmented framework. He proposed a VAR model based on monthly data for $z_t = (\Delta prod_t, rea_t, rpo_t)$, where $\Delta prod_t$ is the percent change in global crude oil production, rea_t denotes an index of monthly global real economic activity in industrial commodity markets based on data for dry cargo bulk freight rates, and rpo_t refers to the real price of oil. The structural VAR representation and the reduced form representations are:

$$\begin{aligned} A_0 z_t &= \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \\ z_t &= \beta + \sum_{i=1}^{24} B_i z_{t-i} + e_t \end{aligned}$$

where ε_t denotes the vector of serially and mutually uncorrelated structural innovations and $e_t = A_0^{-1}\varepsilon_t$. The identification assumptions are a set of linear restrictions on A_0^{-1}, which uniquely map e_t to ε_t. Kilian postulates the following:

$$e_t = \begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \end{pmatrix} = \begin{bmatrix} x & 0 & 0 \\ x & x & 0 \\ x & x & x \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil\ demand\ shock} \end{pmatrix}$$

Kilian motivates the restrictions on A_0^{-1} as follows. Crude oil supply shocks are defined as unpredictable innovations to global oil production. Furthermore, crude oil supply is assumed not to respond to innovations to the demand for oil within the same month. That exclusion restriction is plausible because, in practice, oil-producing countries will be slow to respond to demand shocks given the costs of adjusting oil production and the uncertainty about the state of the crude oil market. Innovations to global real economic activity that cannot be explained based on crude oil supply shocks will be referred to as shocks to the aggregate demand. The model imposes the exclusion restriction that increases in the real price of oil driven by shocks specific to the oil market will not lower global real economic activity immediately but with a delay of at least a month. This restriction is consistent with the sluggish behavior of global real economic activity after each of the major oil price increases in the sample. Finally, innovations to the real price of oil that cannot be explained based on oil supply shocks or aggregate demand shocks by construction will reflect changes in the demand for oil as opposed to changes in the global demand. The latter structural shock will reflect fluctuations in precautionary demand for oil driven by uncertainty about the availability of future oil supplies in particular.

So, to identify oil supply shocks using this identification scheme, I follow a similar set of steps to those taken in identifying monetary policy shocks. Specifically, I extract five latent factors from the large data set describing the economy and impose three additional observable factors, i.e., $z_t = (\Delta prod_t, rea_t, rpo_t)$. I consider the response of all disaggregated price series to an impulse in the global oil supply. The regression results presented in Panel (A) of Table 8 are based on these impulse responses.

Table 1. Calibrating the Benchmark Parameters

Discount factor	$\beta = 0.9975$
Intertemporal elasticity of substitution	$\sigma = 1$
Inverse Frisch elasticity of labor supply	$\eta = 0$
Elasticity of substitution for goods within a sector	$\theta = 8$
Speed of mean reversion of the shock to nominal GDP growth	$\rho_{\upsilon} = 0.50$
St. deviation of nominal GDP growth	$\sigma_{\upsilon} = 0.002$
St. deviation of the idiosyncratic productivity shock	$\sigma_A = 0.01$

This table describes the benchmark monthly calibration of the multi-sector model. The parameter values presented in this table will be used throughout all exercises.

Table 2. Calibrating the Multi-Sector Economy

Industry	$M.X/P.Y$	s	ω	ς	ε	BCR (s)
Manufacturing	0.67	0.24	0.87	0.70	0.51	*n.a.*
Agriculture	0.65	0.26	0.15	0.08	0.02	0.26
Mining	0.50	0.43	0.42	0.09	0.00	0.24
Construction	0.50	0.43	0.88	0.02	0.00	0.39
Services	0.44	0.50	0.92	0.06	0.40	0.40
Utilities	0.41	0.53	0.56	0.05	0.07	*n.a.*

This table describes the sectoral heterogeneity as described in cases 1 to 3 of the calibration exercise. In case 1, s (the share of labor in production function) varies across sectors. In case 2, ω (the frequency of price adjustment) is also heterogeneous. In case 3, ς and ε (the weights in the intermediate input aggregator and consumption basket) also vary.

Table 3. Real Effects of Shocks

	Hom. Econ.	Case 1	Case 2	Case3
Max. relative price	0.0%	7.9%	43.3%	39.1%
Max. std. of the prices	0.0%	3.3%	20.3%	17.7%
Cumulative response of consumption	0.68×10^{-2}	1.11×10^{-2}	2.07×10^{-2}	3.10×10^{-2}
$Var(C) \times 10^4$	0.07	0.15	0.24	0.38

This table summarizes the short-run relative price effects or the extent of short-run monetary non-neutrality in each of the models described in the text. The measure in first row is the maximum relative price across all the sectors at all horizons. Without any heterogeneity in labor shares, this metric would be equal to zero. The second measure (row 2) reports the maximum standard deviation between prices at any horizon t. Rows (3) and (4) report two measures of the non-neutrality which are relevant even in a one-sector economy. Row (3) reports the conditional variance of consumption's response to a monetary policy shock. Row (4) reports the variance of real value-added output when the model is simulated with purely nominal aggregate shocks.

Table 4. Calibrating the Multi-Sector Economy: Decreasing Returns to Scale

Industry	α	γ	DRS	ω	ς	ε
Manufacturing	0.25	0.74	0.99	0.87	0.70	0.51
Agriculture	0.15	0.72	0.87	0.15	0.08	0.02
Mining	0.56	0.56	0.78	0.42	0.09	0.00
Construction	0.38	0.56	0.94	0.88	0.02	0.00
Services	0.37	0.49	0.86	0.92	0.06	0.40
Utilities	0.18	0.46	0.64	0.56	0.05	0.07

This table describes the calibration of the model where decreasing returns to scale are assumed. α and γ denote the share of labor and intermediate inputs in the production function $y_t^j(z) = \left(A_t^j L_t^j(z)\right)^{\alpha_j} M_t^j(z)^{\gamma_j}$ for each industry respectively. The column DRS is the total returns to scale $(\alpha + \gamma)$. ω, ς and ε are calibrated as in Table 2.

Table 5. Real Effects of Nominal Shocks

	DRS
Max. relative price	29.9%
Max. std. of the prices	10.9%
Cumulative response of consumption	4.30×10^{-2}
$Var(C) \times 10^4$	0.47

This table summarizes the short-run relative price effects for the model with decreasing returns to scale. The measures presented are the same as in Table 3. The first row is the maximum relative price across all the sectors at all horizons, the second row reports the maximum standard deviation between prices at any horizon t. Row (3) reports the conditional variance of consumption's response to a monetary policy shock. Row (4) reports the variance of real value-added output when the model is simulated with purely nominal aggregate shocks.

Table 6. Validity of Instruments

Dependent variable: $s.d.(x)$		Dependent variable: $\rho(x)$	
$s.d.(e)$	1.00^{*}	$\rho(e)$	0.28^{*}
	(0.00)		(0.05)
constant	0.00^{*}	*constant*	0.50^{*}
	(0.00)		(0.02)
Observations	154	Observations	154
R^2	1.00	R^2	0.15

This table shows the validity of $s.d.(x_i)$ and $\rho(x_i)$ (properties of the data) as good instruments for the $s.d.(e_i)$ and $\rho(e_i)$ (properties of the estimated VAR errors). Using $s.d.(e_i)$ and $\rho(e_i)$ in the second stage regressions would result in incorrect standard errors.

Table 7. Speed of Price Responses to Monetary Policy Shocks

	Panel A: FAVAR				Panel B: Romer & Romer (2004)			
Dependent variable:	IR_{12}^{MP}				IR_{12}^{MP}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
constant	-1.03^{*}	-1.33^{*}	-1.07^{*}	-1.3^{*}	-2.45^{*}	-2.87^{*}	-2.78^{*}	-2.83^{*}
	(0.05)	(0.07)	(0.13)	(0.18)	(0.07)	(0.09)	(0.12)	(0.11)
pos	-0.41^{*}	-0.33^{*}	-0.27^{*}	-0.21^{*}	-0.30^{*}	-0.22^{*}	$-0.20^{\dagger}$	-0.24^{*}
	(0.09)	(0.08)	(0.07)	(0.07)	(0.13)	(0.11)	(0.12)	(0.12)
$s.d.(x)$		19.70^{*}	18.6^{*}	24.1^{*}		70.6^{*}	69.2^{*}	69.6^{*}
		(.024)	(4.25)	(5.40)		(8.7)	(8.6)	(8.8)
$profit$			$-1.05^{\dagger}$	$-0.94^{\dagger}$			-0.34	
			(0.43)	(0.40)			(0.46)	
$\rho(x)$				0.35^{*}				-0.10
				(0.13)				(0.27)
Observations	153	153	152	152	153	153	152	153
R^2	0.12	0.34	0.38	0.41	0.03	0.28	0.28	0.28

*: Significant at 5% †: Significant at 10%

This table presents the results of the regression $IR_{i,h}^{MP} = \alpha + \beta_1 POS_i + \beta_2 s.d.(x_i) + \beta_3 profit + \beta_4 \rho(x_i) + \varepsilon_i$. Panel (A) presents the results where the dependent variables are the impulse response of sectoral prices to a monetary policy shock identified in a FAVAR model as explained in the text. Panel (B) presents the regression results where impulse responses are computed in response to a monetary policy shock identified using the Romer and Romer (2004) measure of monetary policy shocks. The dependent variables in both cases are measured as the percentage of price decline twelve months after the shock occurs relative to the pre-shock level.

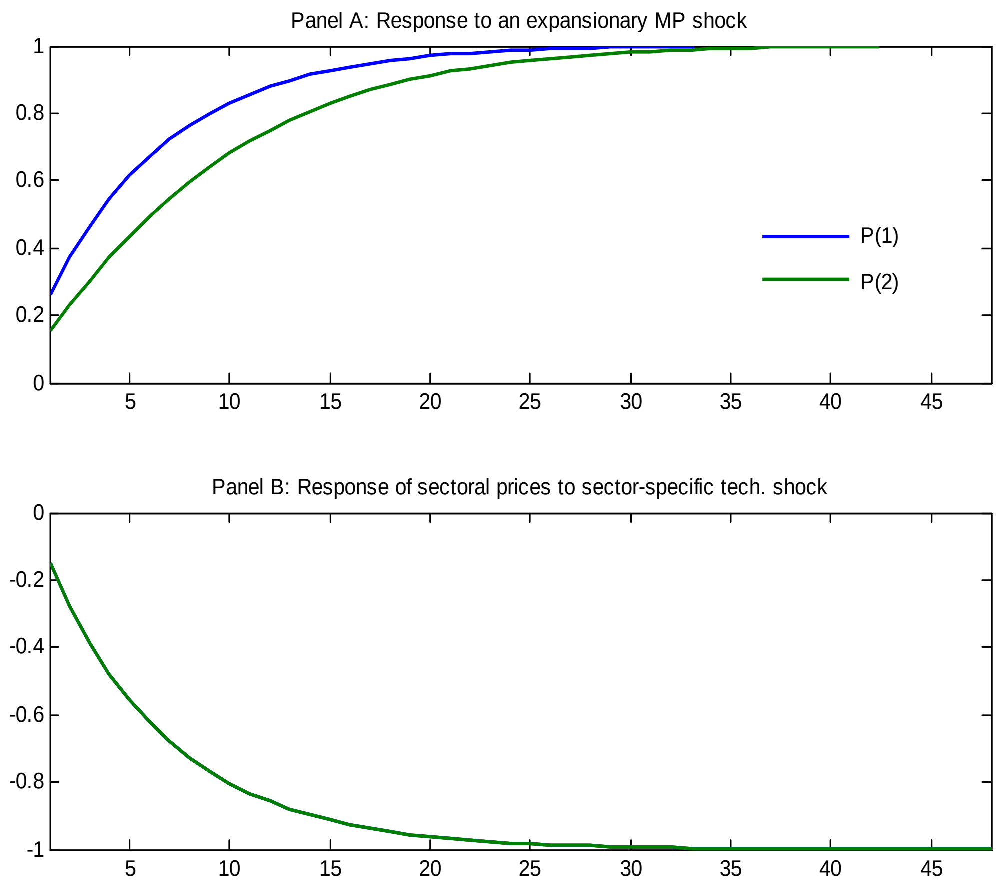
Table 8. Speed of Price Responses to Oil Supply Shocks

	Panel A: FAVAR				Panel B: Historical			
Dependent variable:	$IR_9^O - IR_{12}^O$		IR_9^O		$IR_9^O - IR_{12}^O$		IR_9^O	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
constant	0.07	0.05	-0.96^*	-1.14^*	-0.10^*	-0.10	-2.9^*	-3.13^*
	(0.05)	(0.05)	(0.04)	(0.06)	(0.04)	(0.07)	(0.07)	(0.08)
pos	-0.23^*	-0.22^*	$-0.19^\dagger$	-0.14	$-0.21^\dagger$	$-0.21^\dagger$	-0.22	-0.19
	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)	(0.12)	(0.14)	(0.14)
$s.d.(x)$		1.51		12.3^*		0.17		22.9^*
		(2.4)		(3.4)		(4.6)		(5.0)
energy			0.0^*	0.0^*			2.9^*	$1.94^\dagger$
			0.0	0.0			(1.2)	(1.1)
Observations	153	153	153	153	153	153	153	153
R^2	0.06	0.06	0.04	0.12	0.02	0.03	0.07	0.21

* : Significant at 5% † : Significant at 10%

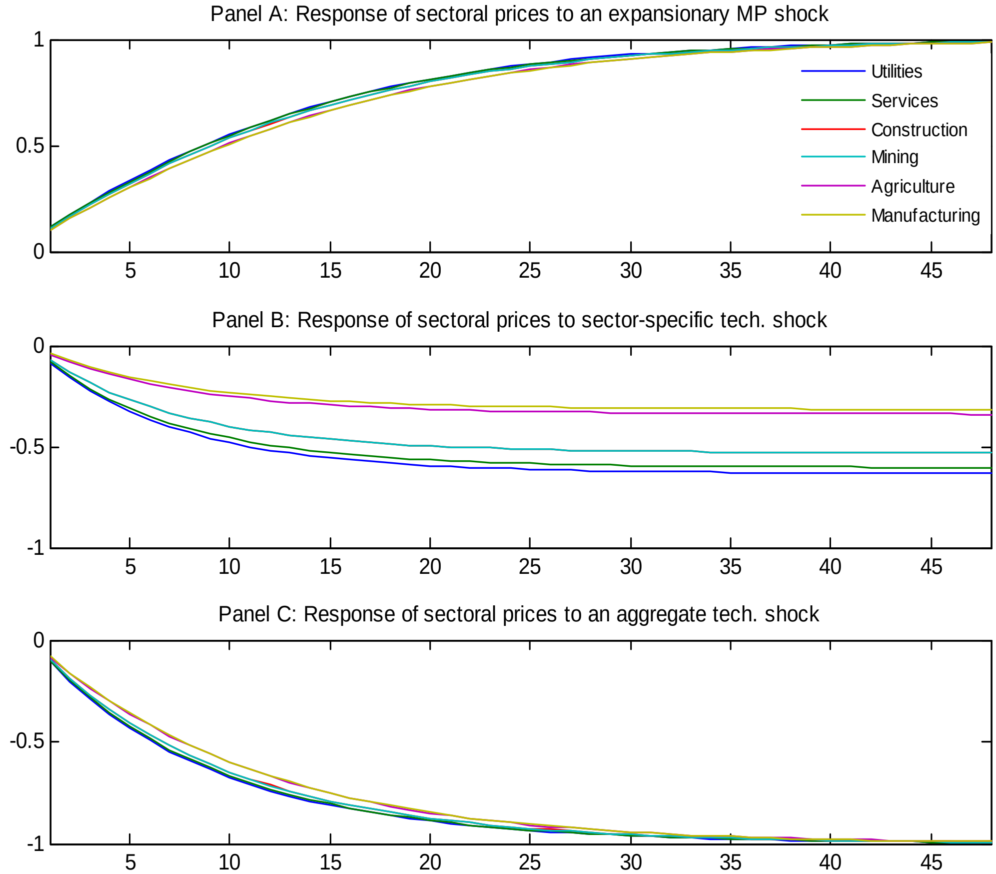
This table presents the following regression results: $IR_{i,h}^O = \alpha + \beta_1 POS_i + \beta_2 s.d.(x_i) + \beta_3 profit + \beta_4 \rho(x_i) + \beta_5 energy + \varepsilon_i$ and $IR_{i,h}^O - IR_{i,m}^O = \alpha + \beta_1 POS_i + \beta_2 s.d.(x_i) + \beta_3 profit + \beta_4 \rho(x_i) + \varepsilon_i$. Panel (A) presents the results where the dependent variables are the impulse response of sectoral prices to an oil supply shock identified in a FAVAR model as explained in the text. Panel (B) presents the regression results where impulse responses are computed in response to a oil supply shock identified using Kilian's historical measure of oil supply shocks. The dependent variables are either the price response between nine months and twelve months after the shock or the percentage of price change twelve months after the shock relative to the pre-shock level.

Figure 1. A Special Two-Sector Economy Example



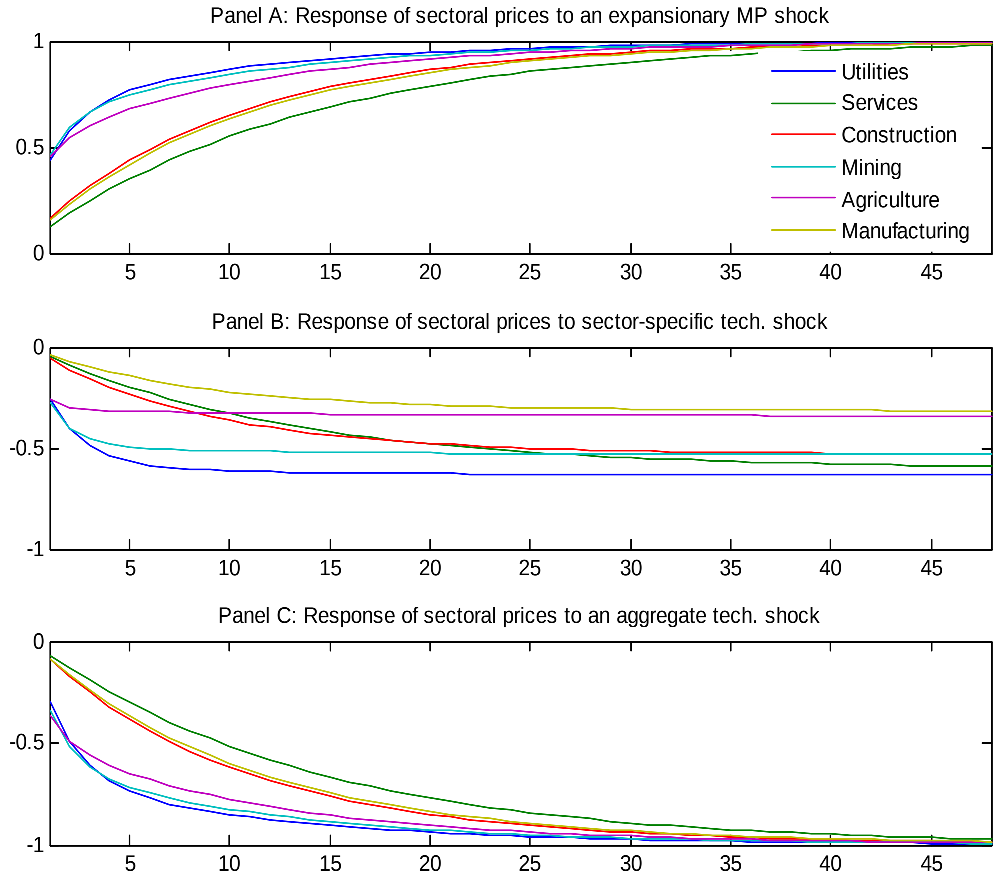
This figure shows the impulse response of the sectoral prices in a special two-sector economy to an expansionary monetary policy shock (Panel (A)) and a positive technology shock (Panel (B)). As argued, the position of a sector along the production chain only matters in response to aggregate shocks.

Figure 2. Heterogeneity in $s_i . \omega_i = 0.85 . \varepsilon_i = \varsigma_i = (1/6)$.



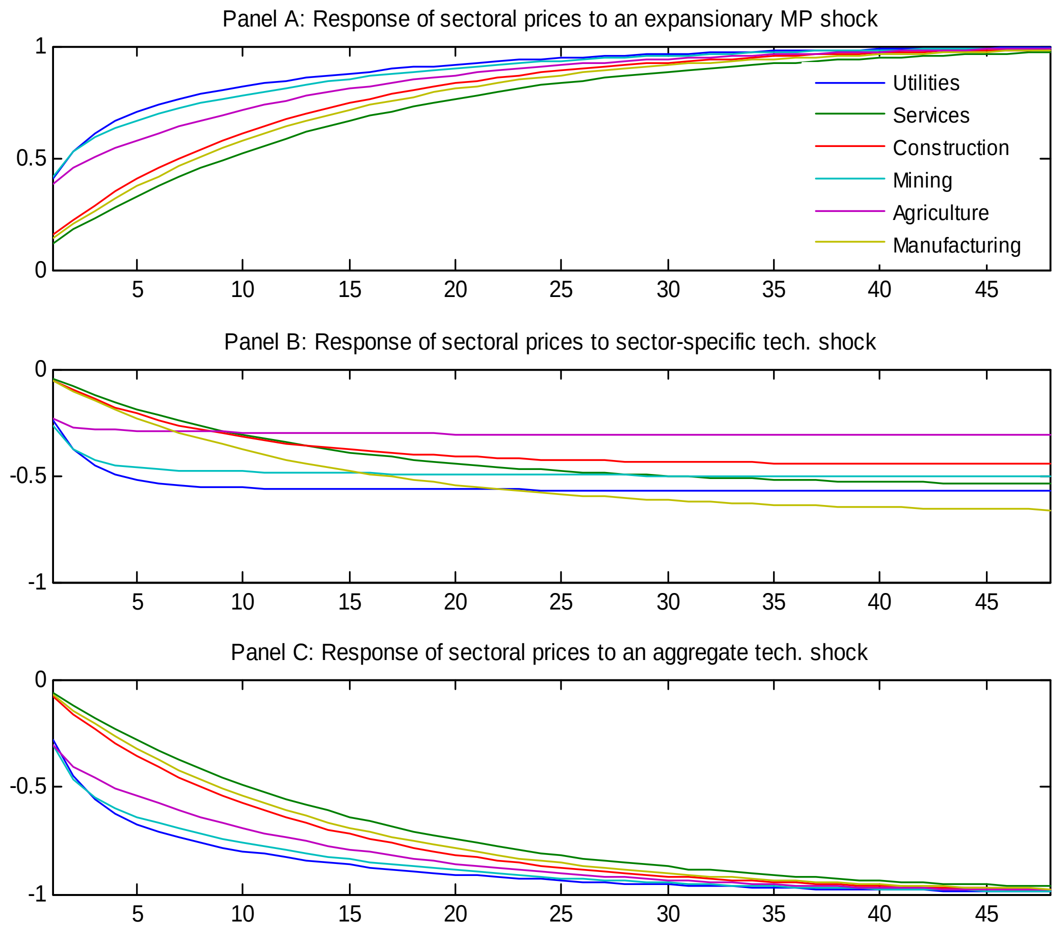
This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C), under Case (1). Sectors only differ in their share of intermediate input use. Frequency of price adjustment and the weight in the intermediate input and consumption baskets are identical.

Figure 3. Heterogeneity in s_i, ω_i. $\varepsilon_i = \varsigma_i = \frac{1}{6}$.



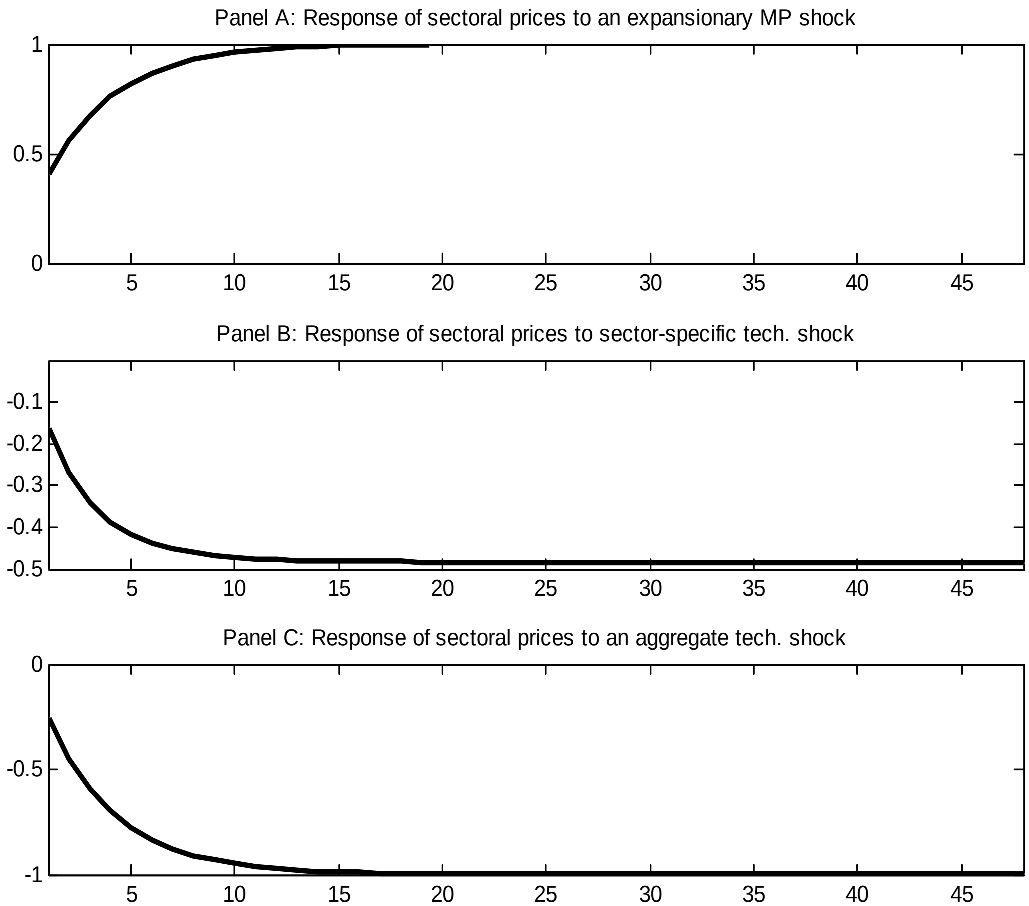
This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C) under Case (2). Sectors differ in their share of intermediate input use and frequency of price adjustment. The weights in the intermediate input and consumption baskets are identical.

Figure 4. Heterogeneity in s_i, ω_i, ε_i and ς_i.



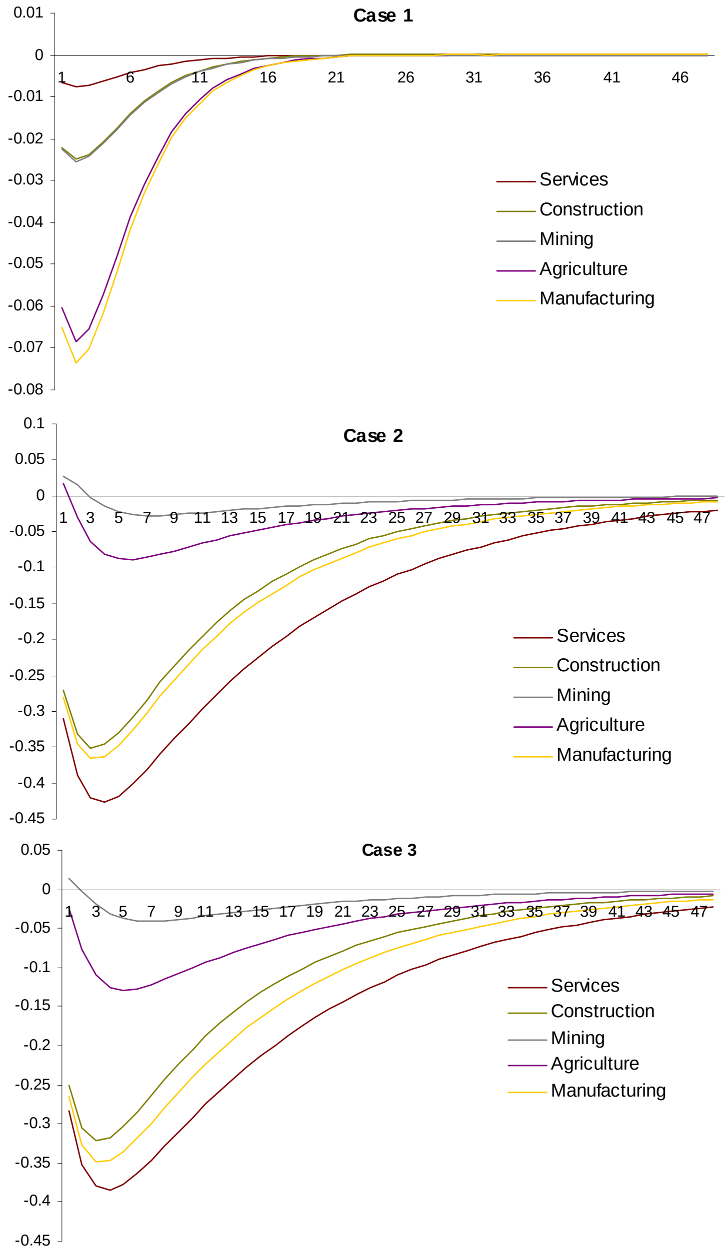
This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C) under Case (3). Sectors only differ in their share of intermediate input use, frequency of price adjustment and the weight in the intermediate input and consumption baskets.

Figure 5. Equivalent Homogeneous Economy: $s_i = 0.38$, $\omega_i = 0.62$, $\varepsilon_i = \varsigma_i = \frac{1}{6}$.



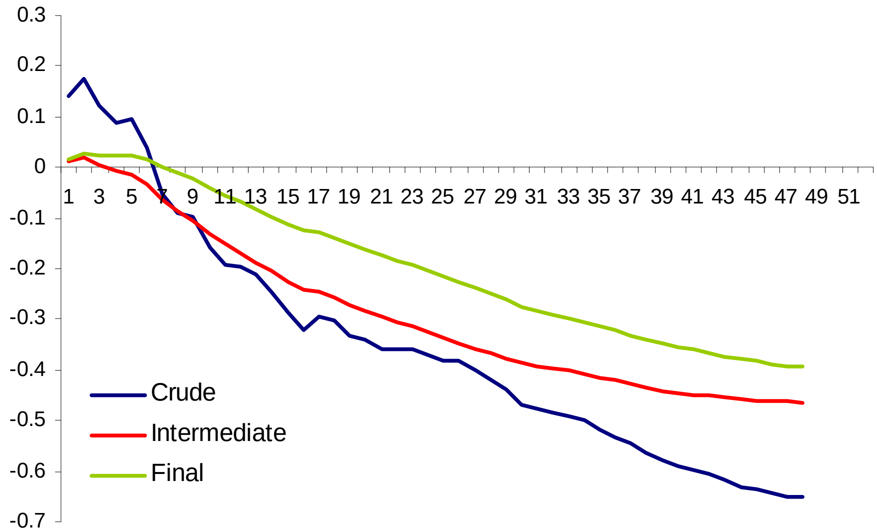
This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C).

Figure 6. Relative Price Effects of a Monetary Policy Shock (sectoral prices relative to Utilities)



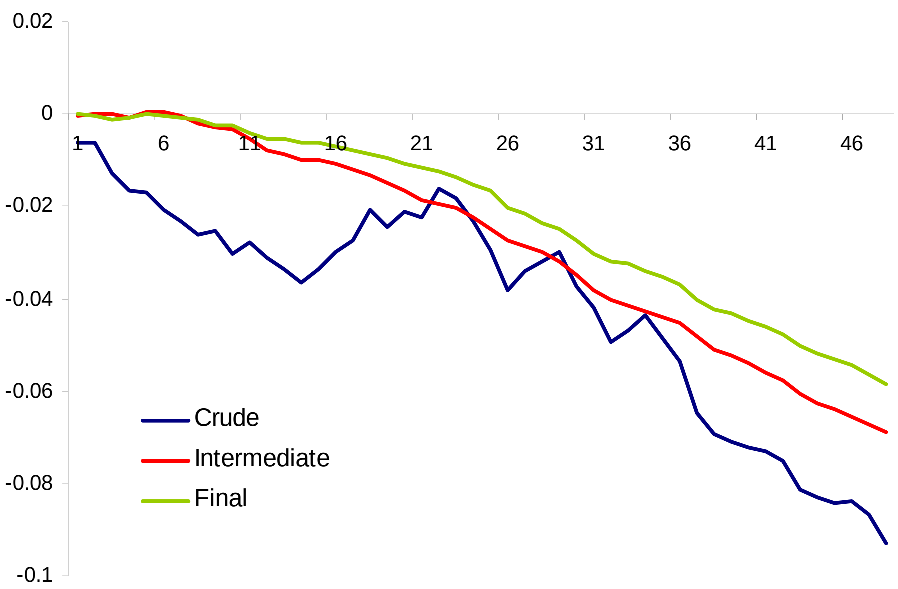
This figure shows the prices of all sectors relative to that of Utilities in response to a monetary policy shock in the three cases analyzed in the text. In cases (2) and (3), where frequency of price adjustment also varies across sectors, Manufacturing sees the largest relative price effect.

Figure 7. The Impulse Response of PPI Aggregates to a Monetary Policy Shock (FAVAR)



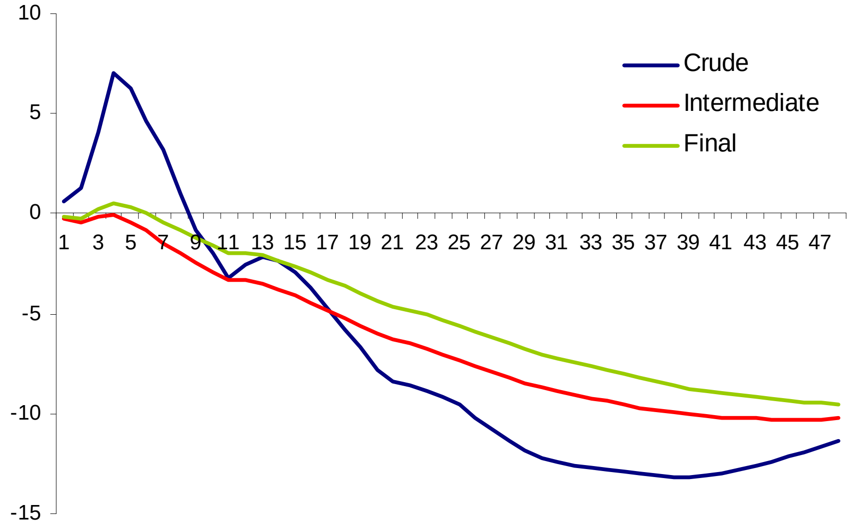
This figure shows the impulse response of three PPI aggregates to a monetary policy shock identified using the FAVAR method.

Figure 8. Response of PPI Aggregates to a Monetary Policy Shock Identified by Romer and Romer (2004)



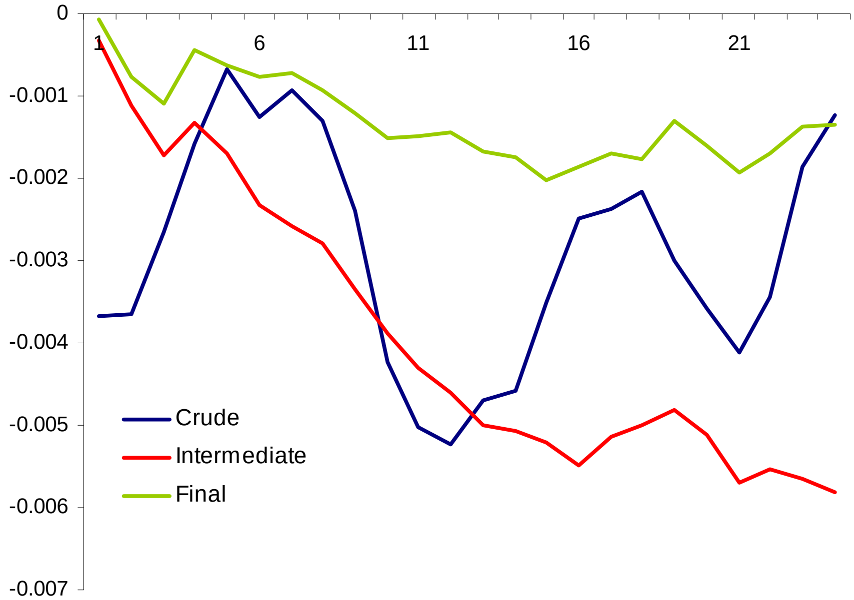
This figure shows the impulse response of three PPI aggregates to a monetary policy shock identified using the Romer and Romer (2004) measure of monetary policy shocks.

Figure 9. Response of PPI Aggregates to an Oil Supply Shock (FAVAR).



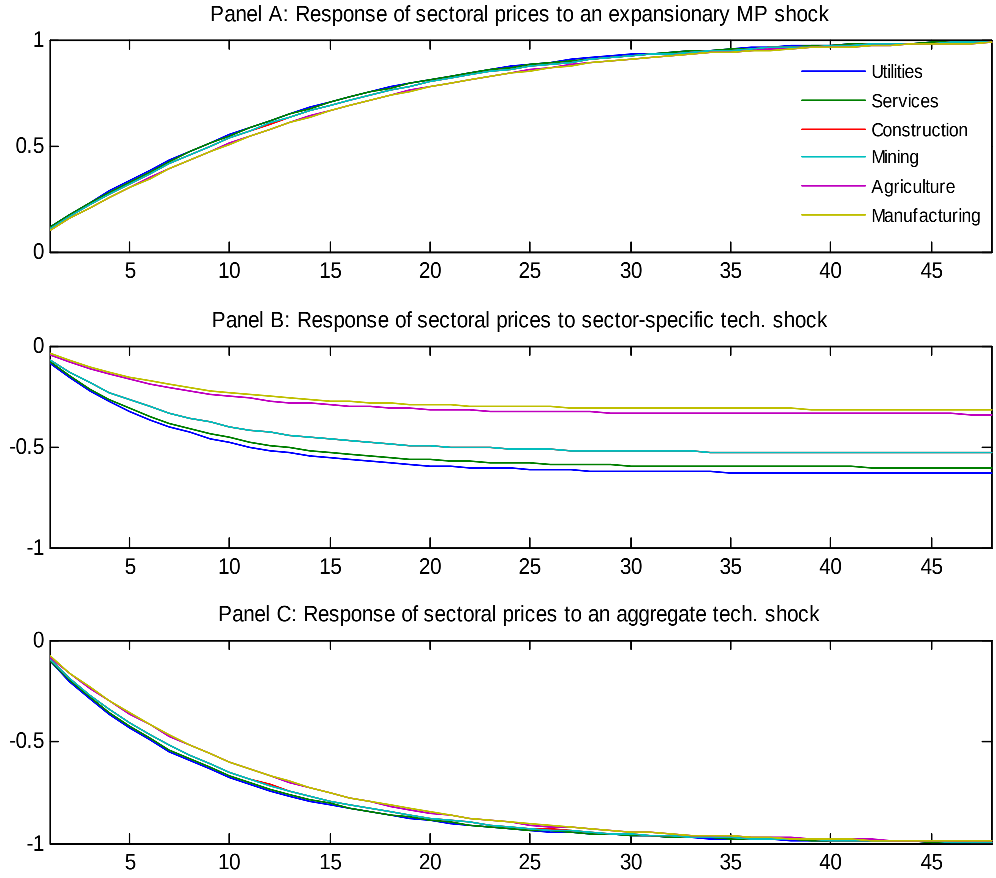
This figure shows the impulse response of three PPI aggregates to an oil supply shock identified in a FAVAR model as explained in the text.

Figure 10. Response of PPI Aggregates to an Oil Supply Shock (Kilian's narrative approach).



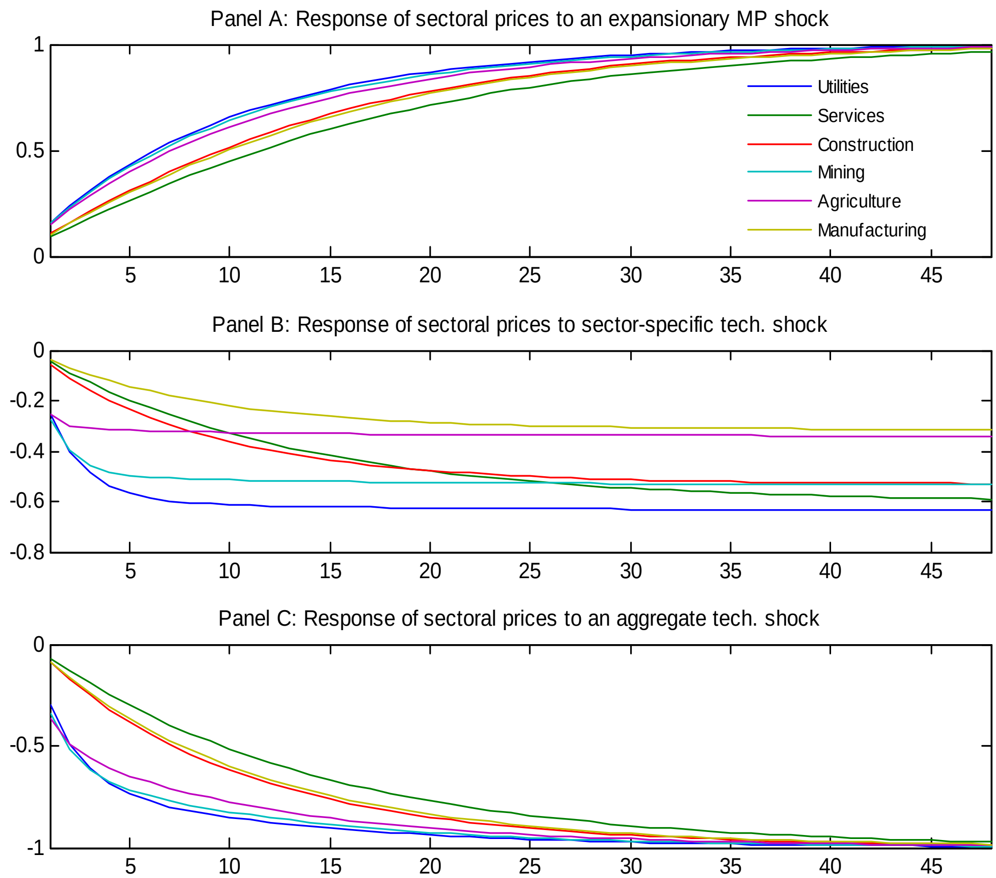
This figure presents the impulse responses of three PPI aggregates to an oil supply shock identified using Kilian's historical measure.

Figure 11. Heterogeneity in s_i. $\omega_i = 0.85.$, $\varepsilon_i = \varsigma_i = \frac{1}{6}$.



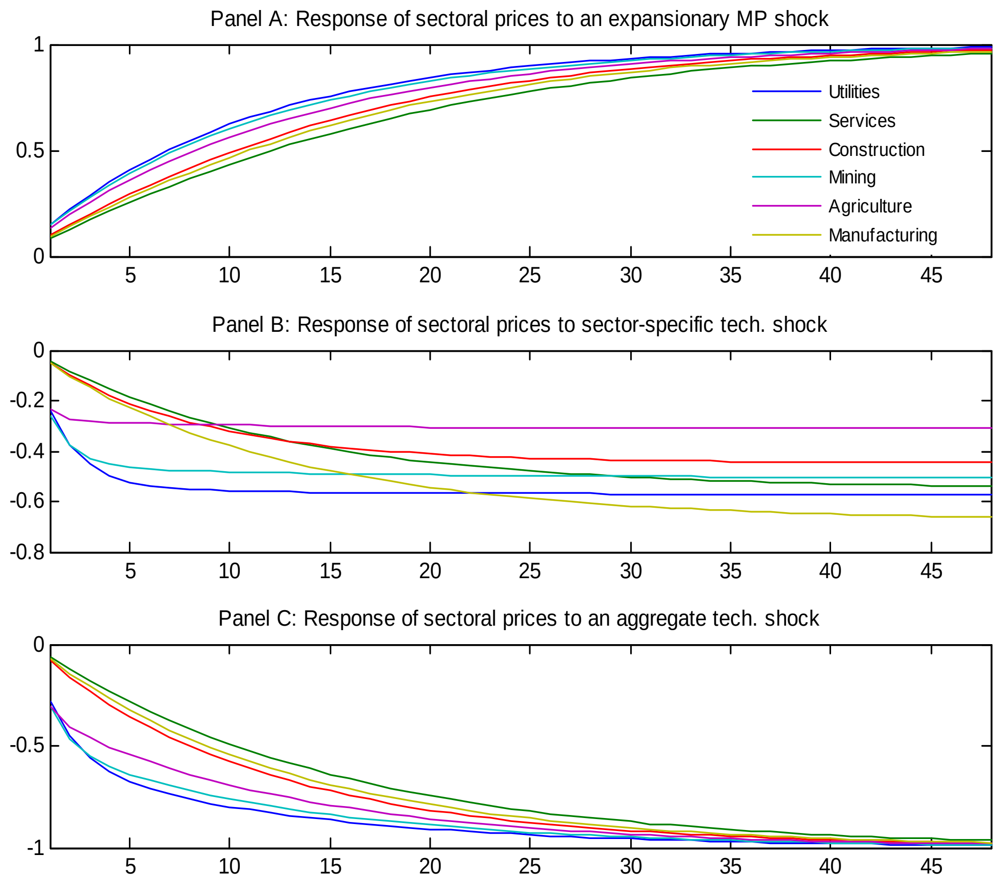
This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C) under Case (1) with wage rigidity. Sectors only differ in their share of intermediate input use. Frequency of price adjustment and the weights in the intermediate input and consumption baskets are identical.

Figure 12. Heterogeneity in s_i, ω_i. $\varepsilon_i = \varsigma_i = \frac{1}{6}$.



This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C) under Case (2) with wage rigidity. Sectors differ in their share of intermediate input use and frequency of price adjustment. The weights in the intermediate input and consumption baskets are identical.

Figure 13. Heterogeneity in s_i, ω_i, ε_i and ς_i.



This figure shows the impulse response of sectoral prices to a monetary policy shock (A), idiosyncratic technology shocks (B) and an aggregate technology shock (C) under Case (3) with wage rigidity. Sectors differ in their share of intermediate input use, frequency of price adjustment and the weights in the intermediate input and consumption baskets.

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