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INVESTMENT PRICE RIGIDITY AND BUSINESS CYCLES

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Abstract. This paper incorporates sticky investment prices in a two-sector monetary model of business cycles. Fit to quarterly U.S. time series, the model suggests that price rigidity in the investment sector is the single most empirically relevant friction to match the data. Sticky investment prices are also important to understand the dynamic effects of technology shocks and their pass-through to the relative price of investment goods.

JEL Codes: C32, E32.

Keywords: investment price rigidity, relative price of investment, multisector DSGE model.

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Résumé Non Technique

Les rigidités de prix — définies comme le processus lent et progressif d'ajustement des prix à la suite de chocs — constituent un ingrédient important de l'analyse macroéconomique. Cette forme de rigidité nominale est au fondement de la nouvelle économie keynésienne et de sa représentation de la politique monétaire. Elle apparaît aussi comme l'un des éléments clés des nouveaux modèles dynamiques d'équilibre général (modèles DSGE), utilisés à des fins de prédiction et d'analyse par les banques centrales. Enfin, sa validité empirique est confirmée par les micro-données, qui suggèrent qu'en dépit de changements fréquents la réponse des prix individuels aux chocs agrégés est très graduelle.

En raison de la prévalence de modèles agrégés à secteur unique, la littérature macroéconomique a porté l'essentiel de son attention sur les rigidités de prix dans le secteur des biens de consommation et ignoré les rigidités potentielles dans le secteur des biens d'investissement. Ainsi, les modèles de référence à deux secteurs intègrent des prix rigides pour les biens de consommation et flexibles pour les biens d'investissement. Cette simplification impose pourtant de fortes contraintes sur les mécanismes internes des modèles, limitant leur capacité à prévoir correctement les réponses de l'économie aux chocs de politique monétaire ou technologiques. De plus, elle est en contradiction avec les données, qui suggèrent que les prix des biens d'investissement sont au moins aussi rigides que ceux des biens de consommation.

Dans ce contexte, la contribution de cet article est de trois ordres.

Premièrement, il démontre l'importance des rigidités de prix dans le secteur de l'investissement dans un modèle DSGE monétaire estimé par techniques bayésiennes. Le modèle comprend deux secteurs, qui produisent respectivement des biens de consommation et d'investissement. En accord avec la littérature académique, le modèle intègre des frictions affectant la réallocation des facteurs de production (travail et capital) d'un secteur à l'autre. Il prend aussi en compte l'existence de rigidités de prix et de salaires dans les deux secteurs. Enfin, il introduit un grand nombre de chocs d'offre et de demande spécifiques à chaque secteur.

Le modèle est estimé sur données trimestrielles américaines. Pour renforcer l'identification, les variables observées sont aussi bien agrégées (consommation, investissement, taux d'intérêt) que spécifiques à chaque secteur (prix, salaires, heures travaillées). Le modèle reproduit bien les propriétés clés des données, notamment les co-mouvements entre variables au cours du cycle économique. Si les frictions réelles et nominales contribuent ensemble à ce bon résultat, les rigidités nominales sont de loin plus importantes quantitativement. De manière remarquable, les rigidités de prix dans le secteur des biens

d'investissement constituent la friction la plus importante, alors même qu'elles sont le plus souvent ignorées dans la littérature DSGE.

Deuxièmement, l'article analyse en détail le rôle des rigidités de prix dans le secteur des biens d'investissement dans la dynamique économique. Ce faisant, il réévalue certains résultats de la littérature concernant l'origine des cycles économiques et les effets macroéconomiques des chocs technologiques et monétaires.

Concernant l'origine des fluctuations économiques, le modèle confirme un résultat de Justiniano, Primiceri et Tambalotti (2011), selon lequel un choc de demande pour les biens d'investissement est la cause principale du cycle des affaires. Une contribution de l'article est donc de démontrer que cette prédiction des modèles DSGE est robuste à l'introduction de rigidités de prix dans le secteur des biens d'investissement.

Les rigidités de prix dans le secteur des biens d'investissement affectent de manière importante la réponse de l'économie aux chocs technologiques. En particulier, le modèle prédit qu'un choc améliorant la productivité dans le secteur des biens de consommation génère une expansion, alors qu'un choc améliorant la productivité dans le secteur des biens d'investissement génère une récession. Ces prédictions, qui correspondent aux résultats de la littérature sur la comptabilité de la croissance, sont nouvelles dans la littérature DSGE quantitative. Le mécanisme économique sous-jacent est intuitif. Avec des prix rigides, une amélioration de la productivité dans le secteur des biens d'investissement rend ces biens relativement chers aujourd'hui par rapport au futur, puisque les entreprises ne peuvent diminuer leurs prix que lentement. La demande en biens d'investissement étant très élastique, elle baisse fortement et génère ainsi une récession qui s'étend à l'ensemble de l'économie.

Concernant les effets des chocs de politique monétaire, le modèle suggère que les rigidités de prix dans les secteurs des biens de consommation et d'investissement jouent un rôle équivalent, probablement à cause du degré de rigidité élevé estimé pour chacun des secteurs. Ainsi, d'après le modèle, si les prix devenaient flexibles dans l'un des secteurs tout en restant rigides dans l'autre, la réponse de l'économie à la politique monétaire resterait qualitativement inchangée.

Troisièmement, l'article analyse les propriétés du prix relatif des biens d'investissement. En l'absence de rigidités de prix dans le secteur des biens d'investissement, la théorie économique prédit que le prix relatif de l'investissement mesure exactement l'écart technologique entre les secteurs des biens de consommation et d'investissement. Cette prédiction s'estompe en présence de rigidités de prix dans le secteur des biens d'investissement. Ainsi, les résultats de l'estimation suggèrent que seulement un cinquième de la variance cyclique du prix relatif des biens d'investissement provient de chocs technologiques, le reste représentant l'effet de chocs de demande. Cette décomposition remet en question la validité d'une approche d'identification des chocs technologiques communément employée dans la littérature.

1. Introduction

Price stickiness matters for macroeconomic outcomes. This form of nominal rigidity underlies the ubiquitous New Keynesian model of monetary policy (Woodford, 2003) and constitutes one of the building blocks of the growing literature on quantitative dynamic stochastic general equilibrium (DSGE) models (Christiano, Eichenbaum, and Evans, 2005; Smets and Wouters, 2007), in which it has proven important to understand the effects of monetary, fiscal, and technology shocks. Finally, it is supported by microeconomic evidence on the behavior of individual prices, which suggests that aggregate prices can be sticky even though micro-level prices change frequently (Kehoe and Midrigan, 2015).

Guided by the widespread use of one-sector models, the DSGE literature has focused on price rigidity in the consumption sector. Even benchmark two-sector models, like Justiniano, Primiceri, and Tambalotti (2010, 2011), feature sticky consumption prices but flexible investment prices. While convenient for aggregation, ruling out nominal frictions in the investment sector imposes strong limitations on the model's internal mechanisms. Indeed, Barsky, House, and Kimball (2007) demonstrate that the propagation of monetary shocks is highly sensitive to the presence of investment price stickiness and Basu, Fernald, and Liu (2012) show that this is also true for technology shocks. Additionally, there is ample empirical evidence that investment prices are indeed sluggish. Bils and Klenow (2004) report that the monthly frequency of price changes for durable goods, typically classified as investment in DSGE models, is virtually the same as that for nondurable goods, close to 30 percent. Moreover, Basu, Fernald, Fisher, and Kimball (2013) find that the pass-through of technology shocks to prices takes several years in the investment sector, again suggestive of strong rigidities. Finally, price sluggishness is a well-known characteristic of the housing market (Case and Shiller, 1989; Iacoviello, 2010).

In this context, my contribution in this paper is threefold. First, I use standard Bayesian methods to confirm the empirical relevance of investment price rigidity within a monetary DSGE model.[1] I consider a two-sector economy, where the sectors produce respectively consumption and investment goods. Building on earlier literature, the model includes reallocation frictions in production factors through imperfect substitution of hours worked and capital services across sectors. Following Barsky, House, and

[1]Estimated business-cycle models with sticky investment prices can be found in the literature, for instance DiCecio (2009), Gortz and Tsoukalas (2013), or Bouakez, Cardia, and Ruge-Murcia (2014). In the first two papers, investment price rigidity is included without much discussion. On the other hand, the latter paper is devoted to sector-specific pricing frictions, but in the context of a much more disaggregated model not comparable to the DSGE literature I address here.

Kimball (2007) and Basu, Fernald, and Liu (2012), it also incorporates sector-specific nominal rigidities, with different frequencies of price and wage adjustments across sectors. Finally, on top of the usual economy-wide shocks to preferences or monetary policy, the model includes a rich array of sectoral disturbances affecting technology, price and wage markups, and government purchases.

I estimate the model using quarterly U.S. time series. To sharpen identification, I include both aggregate and sectoral variables among observables. The estimated model captures the salient features of the data and, in particular, it correctly reproduces aggregate and sectoral macro comovements. Both real reallocation frictions and sector-specific nominal rigidities are needed to obtain a good fit, but the latter are significantly more important. Remarkably, price stickiness in the investment sector constitutes the single most important friction to fit the data, even though it is typically ignored by the DSGE literature.

Second, I analyze the role of investment price rigidity in business-cycle dynamics. In doing so, I reevaluate standard results from the literature about the sources of business cycles and the macroeconomic effects of technology and monetary shocks.

Regarding the sources of business cycles, the model confirms findings from Justiniano, Primiceri, and Tambalotti (2011): shocks to the marginal efficiency of investment (MEI) are the most important drivers of U.S. economic fluctuations. These disturbances affect the transformation of investment goods into installed capital and leave the productivity of investment firms unchanged, thus constituting pure investment demand shifters. My results show that the predominant role of investment demand factors is robust to the introduction of investment pricing frictions.

Furthermore, investment price stickiness constitutes a key mechanism to understand the dynamic effects of technology shocks. The model implies that technology improvements are expansionary in the consumption sector and contractionary in the investment sector. These patterns, consistent with Basu, Fernald, Fisher, and Kimball's (2013) growth-accounting results, have not been previously documented within estimated DSGE models. The underlying economic intuition, developed in Basu, Fernald, and Liu (2012), is straightforward. With sluggish prices, an improvement in investment technology makes current investment expensive relative to the future since firms can only gradually adjust their prices. Investment demand being highly elastic, current demand falls and triggers a generalized recession. Symmetrically, an improvement in consumption technology makes current investment relatively cheaper and thus generates an expansion.

Regarding the effects of monetary policy shocks, the DSGE model suggests that sticky prices in the consumption and investment sectors play equivalent roles, probably because prices appear quite rigid in both sectors. That is, making prices fully flexible in one sector while keeping them sticky in the other would not alter much the economy's response to monetary shocks. This result adds some empirical flesh to Barsky, House, and Kimball's (2007) discussion of the effectiveness of monetary policy in presence of sector-specific pricing frictions.

Third, I examine the link between relative technology shocks and the relative price of investment goods. Extended nominal rigidities break the usual identity between relative technology and the relative price in the model. Notably, according to the estimation results, only one-fifth of the cyclical variance of the relative price of investment is due to technology shocks, while the contribution of markup shocks exceeds 50 percent. This result calls into question the validity of a widespread empirical approach imposing a period-by-period equality between relative technology and the relative price of investment.

Overall, the paper bridges two strands of the macroeconomic literature that have so far evolved mostly in isolation. Specifically, it shows that, when suitably augmented by sticky investment prices, estimated DSGE models à la Justiniano, Primiceri, and Tambalotti (2010, 2011) share with growth-accounting exercises à la Basu, Fernald, Fisher, and Kimball (2013) important predictions about the recessionary character of investment supply shocks and the slow pass-through of technology to relative prices. This agreement between the results of two unrelated identification approaches should bolster confidence about the robustness of the empirical findings.

The paper is organized as follows: Section 2 sets up the DSGE model, while Section 3 describes the estimation procedure and the data. Section 4 reports estimation results, including a discussion of the model fit. Section 5 examines the implications of investment price stickiness for the sources of business cycles, the effects of technology and monetary shocks, and the properties of the relative price of investment. Finally, Section 6 concludes.

2. A Two-Sector DSGE Model

The model builds on Basu, Fernald, and Liu (2012), who extend the medium-scale sticky-price economies from Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2010, 2011) to an explicit two-sector structure. I add to their framework frictions affecting the sectoral allocation of production factors. The economy is populated by seven classes of agents: a final retail sector producing homogeneous consumption and investment goods, two intermediate sectors specializing in producing inputs for the consumption and investment retailers, households, competitive labor packers, monopolistic labor unions, a central bank, and a government. Their decisions are described in turn.

2.1. **Final retail sector.** There are two competitive retailers, one for each sector. They purchase a continuum of differentiated sector-specific intermediate inputs and produce the final consumption and investment goods in quantities Y_t^c and Y_t^i according to

$$Y_t^c = \left[\int_0^1 Y_t^c(j)^{\frac{1}{1+\eta_t^c}} dj\right]^{1+\eta_t^c}, \qquad Y_t^i = \left[\int_0^1 Y_t^i(j)^{\frac{1}{1+\eta_t^i}} dj\right]^{1+\eta_t^i}.$$

The elasticities η_t^c and η_t^i correspond to sector-specific price markup shocks and evolve according to

$$\ln(1+\eta_t^c) = (1-\rho_{\eta c})\ln(1+\eta^c) + \rho_{\eta c}\ln(1+\eta_{t-1}^c) + \epsilon_t^{\eta c} - \theta_c\epsilon_{t-1}^{\eta c},$$
$$\ln(1+\eta_t^i) = (1-\rho_{\eta i})\ln(1+\eta^i) + \rho_{\eta i}\ln(1+\eta_{t-1}^i) + \epsilon_t^{\eta i} - \theta_i\epsilon_{t-1}^{\eta i},$$

with $\epsilon_t^{\eta c} \sim iidN(0,\sigma_{\eta c}^2)$ and $\epsilon_t^{\eta i} \sim iidN(0,\sigma_{\eta i}^2)$. Standard manipulations yield the equilibrium expressions of the aggregate consumption and investment prices:

$$P_t^c = \left[\int_0^1 P_t^c(j)^{-\frac{1}{\eta_t^c}} dj\right]^{-\eta_t^c}, \qquad P_t^i = \left[\int_0^1 P_t^i(j)^{-\frac{1}{\eta_t^i}} dj\right]^{-\eta_t^i}.$$

2.2. **Intermediate sector.** Monopolistically competitive firms produce the intermediate inputs using capital and labor services, according to

$$Y_t^c(j) = K_t^c(j)^{\alpha_c}[\Gamma_t^c L_t^c(j)]^{1-\alpha_c} - \Omega_t^c\Phi_c, \quad Y_t^i(j) = K_t^i(j)^{\alpha_i}[\Gamma_t^i L_t^i(j)]^{1-\alpha_i} - \Omega_t^i\Phi_i.$$

Here, $K_t^x(j)$ and $L_t^x(j)$ denote the amounts of capital and labor services employed by firm j in sector x, while α_x and $\Omega_t^x\Phi_x$ measure the capital share and the fixed production cost. Factor shares may differ across sectors. Ω_t^x is a sector-specific stochastic trend included to ensure proper scaling of the fixed cost along the balanced growth path of the model. Γ_t^c and Γ_t^i are two sector-specific stochastic productivity trends that evolve according to

$$\ln\mu_t^c = (1-\rho_{\mu c})\ln\mu^c + \rho_{\mu c}\ln\mu_{t-1}^c + \epsilon_t^{\mu c},$$
$$\ln\mu_t^i = (1-\rho_{\mu i})\ln\mu^i + \rho_{\mu i}\ln\mu_{t-1}^i + \epsilon_t^{\mu i},$$

with $\mu_t^c = \Gamma_t^c/\Gamma_{t-1}^c$ and $\mu_t^i = \Gamma_t^i/\Gamma_{t-1}^i$.

Unlike much of the literature, I allow technology innovations to be correlated across sectors. This is a natural assumption, as new technologies or management practices may prove relevant for both sectors and trigger simultaneous adoption, or instead embed some specificity and prompt adoption in a single sector. Theoretically, Basu, Fernald, Fisher, and Kimball (2013) show that in an economy where the final sectors use different combinations of intermediate technologies, sector-specific technology processes feature correlated innovations. Therefore, I assume that $[\epsilon_t^{\mu c}\ \epsilon_t^{\mu i}]'$ is $iidN(m,\Sigma)$ with $m = [0\ 0]'$ and

$$\Sigma = \begin{bmatrix} \sigma_{\mu c}^2 & \sigma_\mu \sigma_{\mu c}\sigma_{\mu i} \\ \sigma_\mu \sigma_{\mu c}\sigma_{\mu i} & \sigma_{\mu i}^2 \end{bmatrix}.$$

In the following, I call $\epsilon_t^{\mu c}$ the C shock, and $\epsilon_t^{\mu i}$ the I shock.

In both sectors, firms are subject to nominal pricing frictions à la Calvo (1983). Each period, an intermediate firm in the C sector can reoptimize its price with probability $1 - \xi_{pc}$. Those that cannot do so index their prices to lagged consumption inflation according to

$$P_t^c(j) = \pi_{c,t-1}^{\iota_{pc}} \pi_c^{1-\iota_{pc}} P_{t-1}^c(j),$$

where $\pi_{c,t} = P_t^c / P_{t-1}^c$. Letting $\widetilde{P}_t^c$ denote the optimal price chosen by reoptimizing C firms, the Calvo assumption ensures that the consumption price index evolves in equilibrium according to

$$\left(P_t^c\right)^{-\frac{1}{\eta_t^c}} = (1-\xi_{pc})\left(\widetilde{P}_t^c\right)^{-\frac{1}{\eta_t^c}} + \xi_{pc}\left(\pi_{c,t-1}^{\iota_{pc}} \pi_c^{1-\iota_{pc}} P_{t-1}^c\right)^{-\frac{1}{\eta_t^c}}.$$

Symmetrically, the equilibrium law of motion for the investment price index can be written

$$\left(P_t^i\right)^{-\frac{1}{\eta_t^i}} = (1-\xi_{pi})\left(\widetilde{P}_t^i\right)^{-\frac{1}{\eta_t^i}} + \xi_{pi}\left(\pi_{i,t-1}^{\iota_{pi}} \pi_i^{1-\iota_{pi}} P_{t-1}^i\right)^{-\frac{1}{\eta_t^i}},$$

with transparent notation.

Consolidating the last two equations yields an expression for the relative price of investment goods, $RPI_t = P_t^i / P_t^c$. Absent Calvo frictions, the nominal price in each sector is equal to the product of the exogenous sector-specific markup with the nominal marginal cost. In that case, RPI_t takes the simple form

$$\frac{P_t^i}{P_t^c} \propto \frac{1+\eta_t^i}{1+\eta_t^c} \frac{(\Gamma_t^c)^{1-\alpha_c}}{(\Gamma_t^i)^{1-\alpha_i}} \frac{(W_t^i)^{1-\alpha_i}(R_t^{ki})^{\alpha_i}}{(W_t^c)^{1-\alpha_c}(R_t^{kc})^{\alpha_c}},$$

where W_t^x and R_t^x denote the nominal wage and rental rate of capital for firms in sector x. This expression shows that fluctuations in the relative price of investment originate from three different sources: (i) shifts in relative markups across sectors, (ii) shifts in relative technology across sectors, and (iii) shifts in the unit production cost across sectors. By assumption, points (i) and (ii) relate to exogenous factors in the model. On the other hand, point (iii) implies that all shocks hitting the economy will be endogenously passed to the relative price in presence of limited factor mobility or differences in factor shares. In presence of nominal rigidities, the same logic carries on but the pass-through of non-markup shocks to the relative price of investment may be considerably slower.

That all shocks affect the equilibrium path of the relative price of investment is in sharp contrast with the direct mapping between RPI_t and relative technology typically embedded in two-sector DSGE models. In the economy at hand, such a tight link would arise as a knife-edge case in a restricted specification with price flexibility, perfectly competitive good markets, full factor mobility, and identical factor shares across sectors. I show in the estimation exercise below that such restrictions are strongly rejected by U.S. data.

2.3. **Households.** The economy is populated by a measure one of households. The representative household's lifetime utility function is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_t \left[\frac{(C_t - h\overline{C}_{t-1})^{1-\sigma}}{1-\sigma} \exp\left(\frac{\sigma - 1}{1+\kappa} \left[(L_t^c)^{1+\omega} + (L_t^i)^{1+\omega} \right]^{\frac{1+\kappa}{1+\omega}} \right) \right],$$

where C_t, L_t^c, and L_t^i respectively denote individual consumption and hours worked in the C and I sectors, $\overline{C}_t$ is the average level of consumption in the economy, $\beta \in (0,1)$ is the discount factor, σ is the risk-aversion coefficient, and $h \in (0,1)$ measures external habit formation. As in Horvath (2000), the specification of the disutility of working implies imperfect labor mobility across sectors when $\omega > 0$, allowing for sectoral heterogeneity in wages and hours worked. $\kappa \geq 0$ measures the aggregate elasticity of labor supply, while ζ_t is an intertemporal preference shock that evolves according to

$$\ln \zeta_t = \rho_\zeta \ln \zeta_{t-1} + \epsilon_t^\zeta,$$

with $\epsilon_t^\zeta \sim iidN(0, \sigma_\zeta^2)$.

The real flow budget constraint of the representative household is

$$C_t + RPI_t \left[I_t + \Psi(u_t)\overline{K}_{t-1} \right] + T_t + \frac{B_t}{P_t^c} \leq \frac{\overline{W}_t^c L_t^c + \overline{W}_t^i L_t^i}{P_t^c}$$
$$+ RPI_t \left(r_t^{kc} K_t^c + r_t^{ki} K_t^i \right) + \frac{\Pi_t + R_{t-1}B_{t-1}}{P_t^c}.$$

On the expenditure side, I_t denotes purchases of new investment goods and $\Psi(u_t)\overline{K}_{t-1}$ is the cost of capital utilization. T_t is a lump-sum tax paid to the government, and B_t is holdings of nominal riskless one-period bonds with rate of return R_t. On the income side, $\overline{W}_t^x L_t^x / P_t^c$ is real labor income from sector x, $RPI_t r_t^{kx} K_t^x$ is income from renting capital services to firms in sector x, and Π_t / P_t^c are real profits rebated by firms and labor unions.

The economy-wide stock of physical capital, $\overline{K}_t$, accumulates according to

$$\overline{K}_t = (1-\delta)\overline{K}_{t-1} + \upsilon_t \left[1 - S\left(\frac{I_t}{I_{t-1}} \right) \right] I_t,$$

where $\delta \in [0,1]$ is the depreciation rate. The adjustment cost function $S(.)$ verifies $S(\mu^i) = S'(\mu^i) = 0$ and $S''(\mu^i) = s$. As in Justiniano, Primiceri, and Tambalotti (2011), υ_t is a shock to the marginal efficiency of investment that captures disturbances to the process by which investment goods are transformed into installed capital. This shock acts as a demand shifter in the investment market and evolves according to

$$\ln \upsilon_t = \rho_\upsilon \ln \upsilon_{t-1} + \epsilon_t^\upsilon,$$

with $\epsilon_t^\upsilon \sim iidN(0, \sigma_\upsilon^2)$.

To capture frictions in the sectoral allocation of capital, I use a specification similar to that of hours worked.[2] Namely, letting $K_t = u_t \overline{K}_{t-1}$ denote the amount of capital services available at date t, I assume that

$$K_t = u_t \overline{K}_{t-1} = \left[(K_t^c)^{1+\nu} + (K_t^i)^{1+\nu} \right]^{\frac{1}{1+\nu}},$$

with $\nu \geq 0$. The cost of capital utilization is of $\Psi(u_t)$ units of investment goods per unit of physical capital. The cost function $\Psi(.)$ is normalized so that in steady state, $u = 1$ and $\Psi(1) = 0$. As usual, I parametrize the function Ψ by $\psi \in (0, 1)$ such that $\Psi''(1)/\Psi'(1) = \psi/(1 - \psi)$.

2.4. **Labor market.** Households supply hours worked to sector-specific unions, which differentiate labor services and set nominal wages subject to Calvo frictions. Competitive labor packers purchase those differentiated services and produce the final labor input usable by firms.

2.4.1. *Labor packers.* There are two competitive labor packers in the economy, one for each sector. They purchase a continuum of differentiated sector-specific labor services and produce usable labor inputs according to

$$L_t^c = \left(\int_0^1 L_t^c(u)^{\frac{1}{1+\eta_t^{wc}}} du \right)^{1+\eta_t^{wc}}, \qquad L_t^i = \left(\int_0^1 L_t^i(u)^{\frac{1}{1+\eta_t^{wi}}} du \right)^{1+\eta_t^{wi}}.$$

The two wage markup shocks η_t^{wc} and η_t^{wi} evolve according to

$$\ln(1 + \eta_t^{wc}) = (1 - \rho_{\eta wc}) \ln(1 + \eta^{wc}) + \rho_{\eta wc} \ln(1 + \eta_{t-1}^{wc}) + \epsilon_t^{\eta wc} - \theta_{wc} \epsilon_{t-1}^{\eta wc},$$
$$\ln(1 + \eta_t^{wi}) = (1 - \rho_{\eta wi}) \ln(1 + \eta^{wi}) + \rho_{\eta wi} \ln(1 + \eta_{t-1}^{wi}) + \epsilon_t^{\eta wi} - \theta_{wi} \epsilon_{t-1}^{\eta wi},$$

with $\epsilon_t^{\eta wc} \sim iidN(0, \sigma_{\eta wc}^2)$ and $\epsilon_t^{\eta wi} \sim iidN(0, \sigma_{\eta wi}^2)$.

2.4.2. *Labor unions.* In each sector, labor unions intermediate between households and the labor packer by brand-naming homogeneous hours worked and setting nominal wages. The probability that a particular union in the C sector can reset its nominal wage at period t is constant and equal to $1 - \xi_{wc}$, and nominal wages that are not reoptimized are partially indexed according to

$$W_t^c(u) = (\pi_{c,t-1} \mu_{t-1}^{wc})^{\iota_{wc}} (\pi_c \mu)^{1-\iota_{wc}} W_{t-1}^c(u),$$

[2]This specification of intersectoral frictions also eschews the identification problem pointed by Kim (2003) in presence of both inter- and intratemporal adjustment costs.

where μ_t^{wc} is the equilibrium growth rate in the real sectoral wage W_t^c/P_t^c, with steady-state level $\mu = (\mu^c)^{1-\alpha_c}(\mu^i)^{\alpha_c}$. Letting $\widetilde{W}_t^c$ denote the optimal wage chosen by reoptimizing C unions, the law of motion of the aggregate wage index in the C sector is then

$$(W_t^c)^{-\frac{1}{\eta_t^{wc}}} = (1-\xi_{wc})(\widetilde{W}_t^c)^{-\frac{1}{\eta_t^{wc}}} + \xi_{wc}\left[(\pi_{c,t-1}\mu_{t-1}^{wc})^{\iota_{wc}}(\pi_c\mu)^{1-\iota_{wc}}W_{t-1}^c\right]^{-\frac{1}{\eta_t^{wc}}}.$$

Similar computations deliver the wage equation for the I sector:

$$(W_t^i)^{-\frac{1}{\eta_t^{wi}}} = (1-\xi_{wi})(\widetilde{W}_t^i)^{-\frac{1}{\eta_t^{wi}}} + \xi_{wi}\left[(\pi_{c,t-1}\mu_{t-1}^{wi})^{\iota_{wi}}(\pi_c\mu)^{1-\iota_{wi}}W_{t-1}^i\right]^{-\frac{1}{\eta_t^{wi}}}.$$

2.5. **Central bank.** The monetary authority sets the nominal interest rate according to a Taylor-like rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_r}\left[\left(\frac{\pi_{c,t}}{\pi_c}\right)^{\phi_\pi}\left(\frac{X_t}{\mu X_{t-1}}\right)^{\phi_x}\right]^{1-\rho_r}\gamma_t^m,$$

where X_t is real GDP in consumption units, defined below.[3] The policy rule is shifted by a disturbance γ_t^m that captures both persistent movements in the central bank's inflation target and discretionary monetary shocks. This policy disturbance evolves according to

$$\ln\gamma_t^m = \rho_m \ln\gamma_{t-1}^m + \epsilon_t^m,$$

with $\epsilon_t^m \sim iidN(0,\sigma_m^2)$.

2.6. **Government.** Fiscal policy is Ricardian. The government purchases exogenous amounts of consumption and investment goods, respectively denoted G_t^c and G_t^i, whose final use is not specified. In particular, I do not allow for a productive feedback from the unmodeled stock of public capital. Letting $g_t^c = G_t^c/\Omega_t^c$ and $g_t^i = G_t^i/\Omega_t^i$ denote detrended expenditures, I assume that

$$\ln g_t^c = (1-\rho_{gc})\ln g^c + \rho_{gc}\ln g_{t-1}^c + \epsilon_t^{gc},$$
$$\ln g_t^i = (1-\rho_{gi})\ln g^i + \rho_{gi}\ln g_{t-1}^i + \epsilon_t^{gi},$$

with $\epsilon_t^{gc} \sim iidN(0,\sigma_{gc}^2)$ and $\epsilon_t^{gi} \sim iidN(0,\sigma_{gi}^2)$. Lump-sum taxes T_t adjust to balance the government budget constraint at each date:

$$T_t = G_t^c + RPI_t G_t^i.$$

[3]In theory, the monetary rule could allow for different responses to C inflation, I inflation, growth in the C sector, and growth in the I sector. From an empirical perspective however, this richer policy rule only marginally improves the fit of the model and leaves the main results unchanged. I have thus opted for the simplest specification here.

2.7. **Market clearing.** Market clearing requires that $B_t = 0$, that

$$C_t + G_t^c = Y_t^c,$$
$$I_t + G_t^i + \Psi(u_t)\overline{K}_{t-1} = Y_t^i$$

in the consumption and investment good markets, and that

$$\int_0^1 K_t^c(j)dj = K_t^c, \qquad \int_0^1 K_t^i(j)dj = K_t^i,$$
$$\int_0^1 L_t^c(j)dj = L_t^c, \qquad \int_0^1 L_t^i(j)dj = L_t^i$$

in the factor markets. Because price dispersion does not matter at the first order, aggregate output in each sector relates to production factors according to

$$Y_t^c = (K_t^c)^{\alpha_c}[\Gamma_t^c L_t^c]^{1-\alpha_c} - \Omega_t^c \Phi_c, \qquad Y_t^i = (K_t^i)^{\alpha_i}[\Gamma_t^i L_t^i]^{1-\alpha_i} - \Omega_t^i \Phi_i.$$

In this economy, nominal GDP is defined as $P_t^c(C_t + G_t^c) + P_t^i(I_t + G_t^i)$. Capital utilization costs are accounted for as intermediate consumption and do not show up in this expression. Real GDP in consumption units is then given by

$$X_t = C_t + G_t^c + RPI_t(I_t + G_t^i).$$

2.8. **Identifying investment shocks.** Abstracting from government investment and utilization costs, the physical capital accumulation equation can be written as

$$\overline{K}_{t+1} = (1-\delta)\overline{K}_t + (1-S_t)\upsilon_t \Gamma_t^i[(k_t^i)^{\alpha_i}(L_t^i)^{1-\alpha_i} - \Phi_i],$$

where $k_t^i = K_t^i/\Gamma_t^i$ and $S_t = S(I_t/I_{t-1})$. As in Justiniano, Primiceri, and Tambalotti (2011), this formulation emphasizes that capital accumulation is directly affected by two investment shocks: the I shock Γ_t^i and the MEI shock υ_t. This raises a possible identification problem, that the literature has addressed in various ways. For instance, Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2010) treat the two shocks as a single unobserved disturbance, while Justiniano, Primiceri, and Tambalotti (2011) restrict the behavior of the I shock by imposing a direct mapping between relative technology and the relative price of investment.

Neither of these approaches would work here. As discussed at the end of Section 2.2, price rigidities in both the consumption and investment markets break the link between relative technology and relative price, so Justiniano, Primiceri, and Tambalotti's strategy would not be appropriate. Another possible scheme, exploiting long-run restrictions, is plagued by arbitrariness because there is no compelling reason to attribute permanent effects to a single shock. In particular, while the above model assumes such a clear-cut decomposition with a permanent I shock and a transitory MEI shock, the persistence of the latter, as estimated from the data, can be arbitrarily close to one.

More fundamentally, the difference between I shocks and MEI shocks relates to the supply-demand decomposition of investment fluctuations. Even if the I shock affects demand through general-equilibrium mechanics, it is primarily a supply shock. As such, and following well-known arguments, one expects I shocks to trigger negative comovements between investment production and I hours in this sticky-price economy (Gali, 1999). On the other hand, the MEI shock affects investment demand but leaves I firms' technology unchanged, thereby triggering positive comovements between investment production and I hours. As shown below, the estimated model supports these intuitions, so the I and MEI shocks are effectively identified by the different conditional comovements they imply. Practically, inclusion of sectoral hours series among observables is thus key to separate the two investment shocks during estimation.

3. Bayesian Inference

I solve the model with standard linearization techniques and use Bayesian methods to estimate its parameters. This section discusses the data, the calibration of some parameters, and the specification of prior distributions for the remaining ones.

3.1. **Data.** I estimate the model using eleven observables: real private consumption growth, real private investment growth, real public consumption growth, real public investment growth, hours worked in the C sector, hours worked in the I sector, real wage growth in the C sector, real wage growth in the I sector, inflation in the C sector, growth in the relative price of investment, and a nominal interest rate. I define private consumption as personal consumption expenditures on nondurable goods and services, while private investment includes both expenditures on durable goods and fixed investment. I use standard chain aggregation methods to construct the relevant quantity and price series. All quantities are expressed in per-capita terms. Appendix A provides data sources and describes the link to observables.

My selection of observables differs from that typically used in the DSGE literature in that I include substantial information about the sectoral structure of the economy. Two objectives underlie this choice. First, sectoral observables provide a useful source of identification for sectoral shocks and frictions. For instance, I argued above that observations on I hours were needed to separate out the two investment shocks. Likewise, consolidating the representative consumer's two first-order conditions for labor supply yields

$$\frac{\overline{W}_t^c}{\overline{W}_t^i} = \left(\frac{L_t^c}{L_t^i}\right)^{\omega},$$

an equation that shows it would be difficult to identify ω, the parameter capturing reallocation frictions in labor, without sectoral data on hours and wages.[4] Second, matching sectoral variables helps the model capture both aggregate and sectoral comovements. There are as many structural shocks in the model economy as observables used in estimation.

I demean all series prior to estimation. This procedure ensures that potential discrepancies between the model's implied balanced growth path and the data's low-frequency patterns will not distort inference at the business-cycle frequencies of interest. The approach also implies that steady-state information will not be used for identification, a fact reflected by the calibration of specific parameters. In addition, I remove independent quadratic trends from the two hours series. This is required by hours worked displaying different long-run behavior in the two sectors, with C hours rising significantly more than I hours over the sample, a property the model is not designed to capture.

The estimation sample runs from 1965Q1 to 2008Q3, which is the first quarter in which the nominal interest rate hit the zero lower bound in the U.S. economy.[5]

3.2. **Calibrated parameters.** I keep thirteen parameters fixed during estimation: the subjective discount factor β; the steady-state depreciation rate δ; the four steady-state markup parameters η^c, η^i, η^{wc}, and η^{wi}; steady-state inflation in the C sector π^c; the steady-state growth rates in sector-specific technologies μ^c and μ^i; the factor shares α_c and α_i; and the two steady-state government spending ratios G^c/Y^c and G^i/Y^i. These parameters are difficult to identify without steady-state information as they have little effect on equilibrium dynamics.

Table 1 reports the chosen values for the calibrated parameters. Consistent with the estimates reported in Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2010, 2011), I set $\beta = 0.998$. Together with the calibrated values for π^c, μ^c,

[4]The equilibrium allocation of capital services is characterized by $r_t^{kc}/r_t^{ki} = (K_t^c/K_t^i)^\nu$. Given the absence of data on the return to capital or the sectoral allocation of capital, a symmetric argument implies that identification of ν is somewhat fragile.

[5]The baseline analysis assumes constant structural parameters throughout the sample. However, Beaudry, Moura, and Portier (2015) argue that the cyclical properties of the relative price of investment changed somewhere in the early 1980's. To account for this fact, I also estimate the model over two subperiods, respectively 1965Q1-1979Q2 and 1984Q1-2008Q3. To save on space, the full results are relegated to the technical appendix. As in Smets and Wouters (2007), I find that the second subsample is characterized by lower standard deviations for the exogenous shocks, reflecting the so-called Great Moderation, and higher price and wage rigidity. The results discussed in Sections 4 and 5 are robust to the use of either sample. The most noticeable difference is that the recessionary effect of investment-specific technology shocks is much more short-lived in the first subperiod because of the higher price flexibility.

TABLE 1. Calibrated parameters.

Parameter	Value	Description
β	0.998	Subjective discount factor
δ	0.025	Steady-state depreciation rate
η^c, η^i, η^{wc}, η^{wi}	0.10	Steady-state net good- and labor-market markups
π^c	1.011	Steady-state gross C inflation
μ^c	1.003	Steady-state gross growth rate in C technology
μ^i	1.008	Steady-state gross growth rate in I technology
α_c	0.35	Capital share in the C sector
α_i	0.30	Capital share in the I sector
G^c/Y^c	0.23	Steady-state share of public consumption
G^i/Y^i	0.15	Steady-state share of public investment

and μ^i and with the point estimate for the risk aversion coefficient σ, this choice implies a steady-state annual nominal interest rate of 7.7 percent, somewhat above the sample average of 6.4 percent. I fix the depreciation rate of capital δ at 0.025, a standard choice for quarterly models, and assume 10 percent markups in both goods and labor markets.

I calibrate π^c, μ^c, and μ^i by matching the sample averages for inflation in the C sector, growth in private consumption, and growth in private investment. In particular, there is faster technological progress in the I sector relative to the C sector, as $\mu^i > \mu^c$. The implied steady-state inflation rate in the I sector is 0.7% per quarter, in line with its sample counterpart. Thus, the model matches the steady-state trend in the relative price of investment as well. I use Basu, Fernald, Fisher, and Kimball's (2013) growth-accounting estimates of sectoral capital shares to fix α_c and α_i. They report final-use capital shares equal to 0.36 for consumption-producing firms and to 0.35 for government consumption, so I set $\alpha_c = 0.35$, as well as capital shares ranging from 0.26 to 0.31 for investment-producing firms, which I aggregate into $\alpha_i = 0.30$.[6] Finally, I fix the steady-state ratios of public to private consumption and public to private investment by matching their sample averages.

3.3. **Prior distributions.** I estimate all remaining parameters. The first columns in Tables 2 and 3 display the chosen prior distributions. Most are in line with the previous literature.

Starting with the representative household's preferences, the risk aversion coefficient σ has a prior mean of 1.5, the habit parameter h is centered around 0.6, and the inverse elasticity of labor supply κ fluctuates around 2. The prior distribution for ω, the parameter capturing the elasticity of substitution across hours in the two sectors, has a mean of

[6]Estimation results are not sensitive to imposing $\alpha_c = \alpha_i = 0.30$ in the calibration.

Table 2. Prior and posterior distributions of structural parameters.

Parameter	Prior distribution			Posterior distribution			
	Distribution	Mean	SD	Mode	Mean	5%	95%
Preferences							
σ	Normal	1.50	0.30	1.26	1.29	1.15	1.45
h	Beta	0.60	0.10	0.64	0.64	0.55	0.72
κ	Gamma	2.00	0.75	1.23	1.33	0.73	1.93
ω	Gamma	2.00	0.75	2.77	2.98	1.67	4.21
ν	Gamma	2.00	0.75	0.12	0.15	0.05	0.23
Frictions							
s	Gamma	5.00	1.50	3.97	4.54	3.02	6.06
ψ	Beta	0.50	0.15	0.94	0.92	0.87	0.97
ξ_{pc}	Beta	0.65	0.10	0.78	0.77	0.71	0.82
ι_{pc}	Beta	0.50	0.15	0.18	0.21	0.07	0.34
ξ_{pi}	Beta	0.65	0.10	0.93	0.93	0.90	0.95
ι_{pi}	Beta	0.50	0.15	0.13	0.15	0.05	0.25
ξ_{wc}	Beta	0.65	0.10	0.85	0.84	0.79	0.90
ι_{wc}	Beta	0.50	0.15	0.11	0.14	0.05	0.23
ξ_{wi}	Beta	0.65	0.10	0.98	0.97	0.95	0.99
ι_{wi}	Beta	0.50	0.15	0.18	0.21	0.07	0.34
Monetary policy							
ρ_r	Beta	0.70	0.10	0.77	0.78	0.74	0.81
ϕ_π	Normal	1.70	0.25	1.91	1.98	1.73	2.20
ϕ_x	Normal	0.40	0.15	0.72	0.72	0.57	0.88

Note. The posterior distribution is constructed from the random-walk Metropolis-Hastings algorithm with a single chain, keeping $500,000$ draws after a burn-in period of size $1,000,000$. The acceptance rate is close to 0.32 and standard tests confirm convergence to a stationary distribution.

2, somewhat above the unit value estimated by Horvath (2000) in a more disaggregated model. Indeed, a prior predictive analysis conducted before estimation emphasized the role of large ω values in generating sectoral comovement in hours. However, to let the data speak as much as possible, I adopt a fairly diffuse gamma prior with a standard deviation of 0.75. I use an identical prior for ν, the parameter quantifying sectoral frictions in capital reallocation.

Prior distributions for other friction parameters are quite standard. In particular, I choose beta distributions centered at 0.65 for the four Calvo coefficients. Regarding monetary policy, I assume that the three parameters of the Taylor rule, ρ_r, ϕ_π, and ϕ_x, respectively fluctuate around 0.7, 1.7, and 0.4.

TABLE 3. Prior and posterior distributions of shock parameters.

Parameter	Prior distribution			Posterior distribution			
	Distribution	Mean	SD	Mode	Mean	5%	95%
Persistence coefficients							
$\rho_{\eta c}$	Beta	0.50	0.20	0.91	0.91	0.87	0.95
$\rho_{\eta i}$	Beta	0.50	0.20	0.81	0.79	0.68	0.89
$\rho_{\mu c}$	Normal	0.00	0.20	0.20	0.19	0.09	0.30
$\rho_{\mu i}$	Normal	0.00	0.20	0.02	0.02	−0.08	0.13
ρ_{υ}	Beta	0.50	0.20	0.54	0.54	0.45	0.64
ρ_{ζ}	Beta	0.50	0.20	0.93	0.92	0.88	0.96
$\rho_{\eta wc}$	Beta	0.50	0.20	0.97	0.96	0.94	0.99
$\rho_{\eta wi}$	Beta	0.50	0.20	0.93	0.92	0.87	0.97
ρ_{m}	Beta	0.50	0.20	0.09	0.11	0.03	0.19
ρ_{gc}	Beta	0.50	0.20	0.97	0.97	0.95	0.98
ρ_{gi}	Beta	0.50	0.20	0.96	0.95	0.93	0.98
MA coefficients for markup shocks							
θ_c	Beta	0.50	0.20	0.60	0.58	0.42	0.74
θ_i	Beta	0.50	0.20	0.59	0.54	0.33	0.74
θ_{wc}	Beta	0.50	0.20	0.83	0.79	0.70	0.88
θ_{wi}	Beta	0.50	0.20	0.84	0.80	0.69	0.91
SDs of innovations							
$1000\sigma_{\eta c}$	InvGamma	2.00	4.00	2.64	2.76	2.19	3.32
$1000\sigma_{\eta i}$	InvGamma	2.00	4.00	2.13	2.21	1.69	2.70
$1000\sigma_{\mu c}$	InvGamma	2.00	4.00	9.02	9.17	8.36	9.98
$100\sigma_{\mu i}$	InvGamma	2.00	4.00	2.22	2.25	2.05	2.45
$100\sigma_{\upsilon}$	InvGamma	2.00	4.00	5.77	6.44	4.70	8.15
$100\sigma_{\zeta}$	InvGamma	2.00	4.00	2.19	2.31	1.88	2.74
$1000\sigma_{\eta wc}$	InvGamma	2.00	4.00	3.08	3.19	2.65	3.71
$1000\sigma_{\eta wi}$	InvGamma	2.00	4.00	1.79	1.83	1.34	2.30
$1000\sigma_{m}$	InvGamma	2.00	4.00	2.53	2.58	2.31	2.84
$100\sigma_{gc}$	InvGamma	2.00	4.00	1.25	1.27	1.15	1.38
$100\sigma_{gi}$	InvGamma	2.00	4.00	2.62	2.64	2.41	2.86
Correlation of technology innovations							
σ_{μ}	Beta	0.50	0.20	0.30	0.30	0.19	0.41

Turning to parameters defining the shocks, I use beta distributions centered at 0.5 for most persistence coefficients. The autocorrelations of the technology processes are two exceptions: because Γ_t^c and Γ_t^i already feature unit roots, I use normal priors centered at zero for the autocorrelations of their growth rates. To ease estimation, I also use prior predictive checks to rescale the standard deviations of all shocks to be of similar order of magnitude. Finally, I base the prior distribution for σ_μ, the correlation coefficient between sector-specific technology innovations, on estimates in Basu, Fernald, Fisher, and Kimball (2013). They report annual correlations between utilization-adjusted changes in C and I technologies ranging between 0.52 and 0.58, so I choose a beta prior with mean 0.5 and standard deviation 0.2 for σ_μ.

4. Estimation Results

This section presents the estimation results. I report parameter estimates and posterior distributions. I also discuss the ability of the model to capture the salient properties of the data.

4.1. **Posterior distributions.** The last columns in Tables 2 and 3 report the posterior modes, means, and 90% probability intervals for the estimated parameters. All seem well identified from the data.

On the preference side, the point estimate of the risk aversion coefficient is equal to 1.26, above the value of one that would correspond to a logarithmic specification. The representative household also displays a moderate degree of habits in consumption, with a point estimate of h close to its prior mean at 0.64. The estimated Frisch elasticity of labor supply is close to 0.8, in the range of the microestimates reviewed in Rios-Rull, Schorfheide, Fuentes-Albero, Kryshko, and Santaeulalia-Llopis (2012). The point estimate of ω is equal to 2.77, well above its prior mean. This suggests that the model needs large labor adjustment costs to fit the data. On the other hand, reallocation frictions in capital services seem unimportant, as the estimated value of ν is close to zero. These findings are consistent with the view that capital markets are more integrated than labor markets. Also, the data are strongly informative about both ω and ν, whose posterior distributions are much tighter than the priors.

Turning to the Calvo coefficients, prices are reoptimized on average once every four quarters in the C sector, and once every fourteen quarters in the I sector.[7] Since all prices in the model change every period through indexation, this low frequency of price optimization does not translate into extreme price sluggishness. Also, the model abstracts from strategic complementarities in price setting, which offer a mechanical way to lower estimates of Calvo coefficients in linearized DSGE models (Eichenbaum and Fisher, 2007). Overall, it is interesting that the data suggest higher price rigidities in the I sector since the DSGE literature usually assumes that $\xi_{pi} = 0$. Turning to wages,

[7] That consumption prices are changed more frequently than investment prices is consistent with the estimates from DiCecio (2009).

there is also more rigidity in the I sector than in the C sector, so again the usual assumption of an aggregate labor market hides substantial sectoral heterogeneity. All estimated indexation coefficients are quite low.

The estimated Taylor rule is consistent with a large empirical literature, as the central bank reacts strongly to both C inflation and output growth. There is some interest rate smoothing and it is interesting to note that, given the estimated policy rule, the model does not need a persistent monetary policy disturbance. Other forcing processes, for instance the four markup shocks, the preference shock, and the two government spending shocks, display strong autocorrelations. Finally, the estimated correlation between quarterly sectoral technology disturbances is equal to 0.30, only about half the value obtained by Basu, Fernald, Fisher, and Kimball (2013). While differences in datasets and identification strategies explain this discrepancy, the dynamic responses of the main macro aggregates to sectoral technology shocks estimated by the Bayesian DSGE approach, discussed in Section 5.2.2, share important properties with those identified by Basu, Fernald, Fisher, and Kimball.

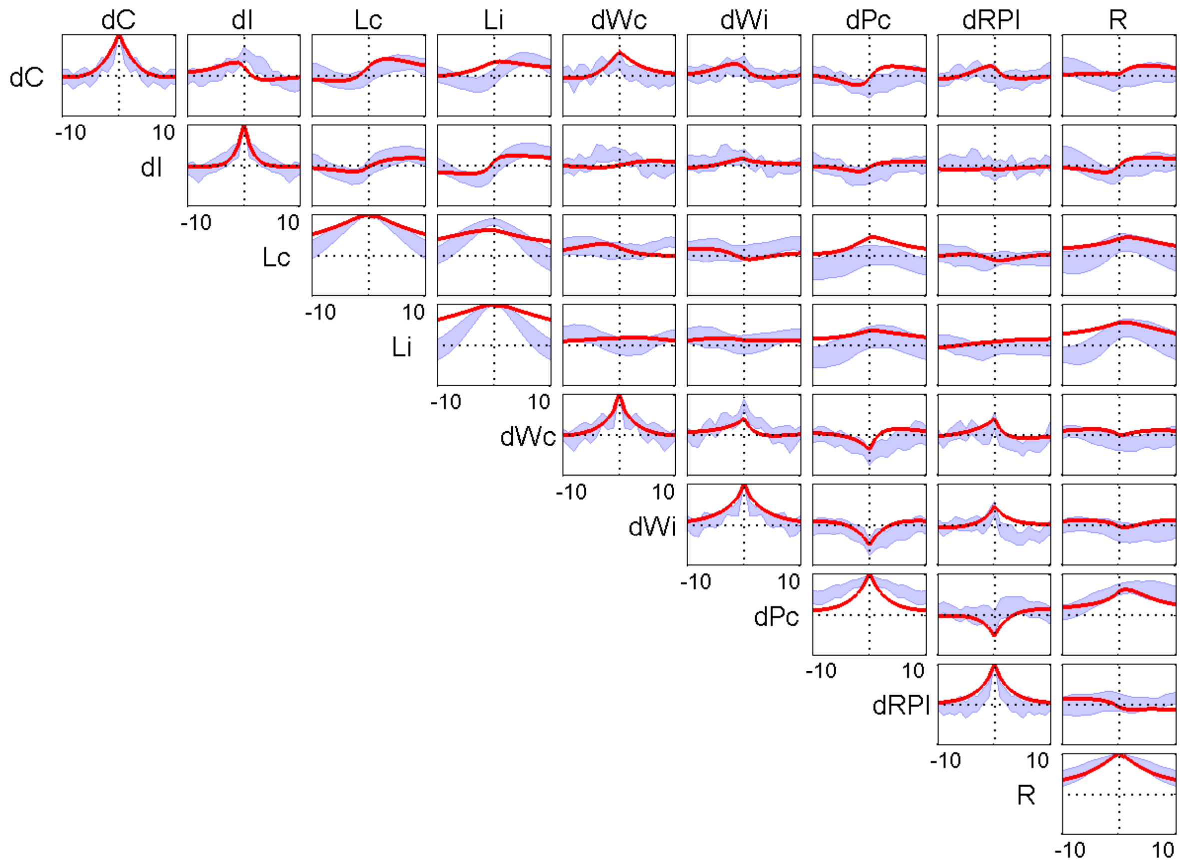
4.2. **Model fit.** To assess the ability of the model to fit the data, Figure 1 compares the theoretical and empirical cross-correlation functions for observables.[8] Solid red lines represent model-based moments computed at the posterior mode, while shaded bands represent 90% GMM confidence intervals centered around the empirical correlations.

A likelihood-based estimator tries to match the entire autocovariance function of the data, so it is not surprising that the estimated model cannot simultaneously fit all moments. However, the general picture is satisfactory and suggests that the model captures the salient properties of the U.S. economy. Plots on the diagonal show that for most variables, the own correlation structure is accurately reproduced. The biggest discrepancies between the data and the model are the overestimated persistence of I hours and the underestimated persistence of C inflation. All other model autocorrelations fall within the empirical confidence bands.

In terms of macro comovements, the correlation patterns between consumption and investment on the one hand, and C hours and I hours on the other, are matched well. In particular, the growth rates of consumption and investment are positively correlated, as are equilibrium hours in the two sectors. The only disparity relates to investment growth: while it leads consumption growth by one quarter in the model, it does not in the data. Also, the dynamic correlations between physical output and labor input are

[8] To increase readability, I omit the two government spending series from the figure. Their cross-correlation functions with other variables are essentially zero at all leads and lags, a fact correctly captured by the model.

Figure 1. Cross-correlations at +/- 10 periods: Model vs. data.



Notes. Solid red lines represent model-based cross-correlograms, evaluated at the posterior mode, while shaded bands represent 90% GMM confidence intervals centered around the empirical correlations, which are not themselves displayed.

reproduced well for both sectors. The model thus does a good job replicating business-cycle comovements at the sectoral level. Finally, the model accounts well for the empirical properties of the relative price of investment goods.

5. Macroeconomic Effects of Investment Price Stickiness

This section demonstrates the importance of investment price stickiness for business-cycle analysis. First, I show that nominal rigidity in the investment sector is the single most important friction in terms of fitting the data, suggesting that it constitutes a powerful propagation mechanism. Second, I confirm this idea by studying how investment price sluggishness affects inference about the sources of macro fluctuations and the effects of structural economic shocks in the model. Finally, I examine the drivers of the relative price of investment in this economy and conclude against the common view that supply shocks predominate.

5.1. **The role of investment price rigidity.** I start by formally assessing the empirical role of investment price stickiness in terms of fitting the data. Indeed, since the model includes many frictions, rigid investment prices may not turn out to be important to capture the dynamics of U.S. time series. To show that they do matter, I reestimate the model shutting off specific channels one at a time and evaluate the relative fit of the restricted specifications using Bayes factors. This is a demanding test of the relevance of individual frictions, since it allows other parameters to adjust to compensate as much as possible for the excluded feature. Therefore, only mechanisms which cannot be replaced by others will stand out as important.

Table 4 reports the log-marginal data densities and Bayes factors comparing the baseline model with several restricted alternatives. With one exception, richer models are always preferred, suggesting that most of the frictions considered are useful to fit the data. Still, Bayes factors especially emphasize the empirical relevance of nominal frictions. Among them, investment price rigidity is associated with the highest factor, thus standing out as the single most important model mechanism. Again, it is important to note that investment price stickiness matters more to fit the data than consumption price rigidity, as macro models usually only include the latter.

As expected, removing nominal rigidities deteriorates the model's ability to fit the behavior of prices and wages. Without I-price rigidity, the model is not able to capture the persistence of the relative price of investment, or its comovements with other variables. Compared to the benchmark specification, the restricted model also does worse at reproducing the correlation between consumption and investment growth, as the latter is now predicted to lead consumption growth by two quarters. Without C-price stickiness, the model underestimates the persistence of C inflation and misses the autocorrelation structure of the two sectoral real wage series. Without nominal wage inertia, the model has difficulties matching the persistence of wages. In addition, a model without wage stickiness in the I sector generates a near zero correlation of hours worked across the C and I sectors, while these are strongly positively correlated in the data.

It is also interesting to examine real rigidities, and I focus on the role of reallocation frictions. As is clear from the estimate of κ, labor reallocation frictions matter and removing them generates a significant loss of fit. In particular, the model without labor frictions counterfactually predicts a negative correlation between C and I hours, as households can now easily shift labor between sectors. Therefore, labor adjustment costs are needed to capture the positive sectoral comovement of hours worked. On the other hand, capital frictions do not seem important and, indeed, removing them improves the

Table 4. Model fit comparisons.

Model specification	Restriction	Log-marginal data density	Bayes factor relative to baseline
Baseline	—	6,788	1.0
No investment price stickiness	$\xi_{pi} = \iota_{pi} = 0$	6,558	exp(230)
No consumption price stickiness	$\xi_{pc} = \iota_{pc} = 0$	6,666	exp(122)
No investment wage stickiness	$\xi_{wi} = \iota_{wi} = 0$	6,579	exp(209)
No consumption wage stickiness	$\xi_{wc} = \iota_{wc} = 0$	6,699	exp(89)
No reallocation friction in labor	$\omega = 0$	6,770	exp(18)
No reallocation friction in capital	$\nu = 0$	6,805	exp(−15)

Notes. Log-marginal data densities computed using the Laplace approximation.

marginal data density. However, this finding should be considered with caution given the lack of information about the sectoral allocation of capital in the data.

5.2. **The economics of investment price rigidity.** I now examine in more detail the economic mechanisms through which price rigidity in the investment sector affects the model dynamics. In doing so, I revisit some classic results regarding the sources of business cycles and the aggregate effects of technology and monetary shocks.

5.2.1. *Sources of business cycles.* I first ask whether inference about the sources of aggregate fluctuations is sensitive to the inclusion of investment price stickiness in the model. With this objective in mind, Table 5 provides the variance decomposition for seven key variables: output (in consumption units), consumption, investment, total hours, hours in the C sector, hours in the I sector, and the relative price of investment. I include sectoral hours to shed light on the sectoral dimension of the data, and the relative price of investment to assess the common view that its movements reflect relative technology shocks. I focus on business-cycle frequencies, as obtained from the HP filter with smoothing parameter 1,600.

Two results stand out. First, shocks to investment efficiency explain the bulk of short-run fluctuations in investment and hours worked: the MEI shock accounts for 64 percent of the cyclical variance of private investment and about 50 percent of that of total hours. It also represents one third of business-cycle movements in aggregate output. These statistics confirm Justiniano, Primiceri, and Tambalotti's (2011) view that shocks to investment demand have been the key drivers of macro fluctuations in the postwar U.S. economy. Second, the restricted model without investment price stickiness attributes the same predominant role to MEI shocks. Thus, adding pricing frictions in the investment sector does not much affect inference about the sources of business cycles.

TABLE 5. Posterior variance decomposition at business-cycle frequencies.

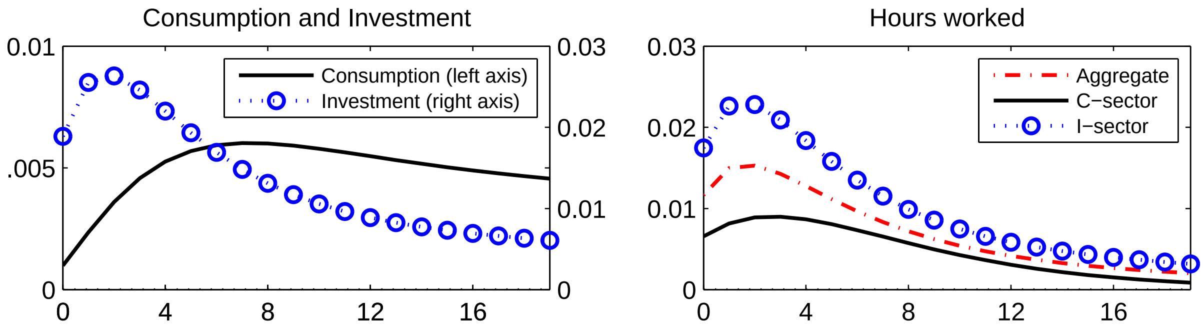
Innovation	$\ln X_t$	$\ln C_t$	$\ln I_t$	$\ln L_t$	$\ln L_t^c$	$\ln L_t^i$	$\ln RPI_t$
			MEI shock				
ϵ^{υ}	29	13	64	49	16	52	4
			C and I technology shocks				
$\epsilon^{\mu c}$, $\epsilon^{\mu i}$	32	20	5	19	14	22	17
			C price markup shock				
$\epsilon^{\eta c}$	16	21	3	10	24	4	20
			I price markup shock				
$\epsilon^{\eta i}$	5	4	11	7	3	9	40
			C wage markup shock				
$\epsilon^{\eta wc}$	4	6	1	2	10	0	2
			I wage markup shock				
$\epsilon^{\eta wi}$	1	0	1	1	0	1	2
			Preference shock				
ϵ^{ζ}	9	25	12	4	15	7	10
			Monetary shock				
ϵ^{m}	3	9	3	7	13	4	5
			Government C and I spending shocks				
ϵ^{gc}, ϵ^{gi}	1	1	0	2	5	1	0

Notes. Decomposition computed at the posterior mode using the HP filter with smoothing parameter equal to $1,600$ to extract the business cycle. Because they are correlated, the two technology shocks appear together. Columns may not sum to 100 because of rounding errors.

To understand this prevalence of MEI shocks, Figure 2 reports the dynamic responses of consumption, investment, and hours worked to a positive innovation to the marginal efficiency of investment. The shock induces an economy-wide expansion, as hours worked in both sectors positively comove with the quantities of C and I goods. The economic logic is simple. In this sticky-price model, output and employment are demand determined in the short run. By stimulating investment demand, the MEI shock triggers a rise in investment and I hours, and the resulting increase in household income boosts consumption and thus C hours. The positive comovement between investment and I hours after the shock is consistent with the argument developed in Section 2.8.

While investment price rigidity has little effect on the estimated role of MEI shocks, it matters more for assessing the contributions of technology shocks. According to the full model, they account for a moderate share of business-cycle movements, representing about 30 percent of the fluctuations in output and 20 percent for consumption and hours worked. However, they do not explain much of investment movements. Interestingly, these contributions are reversed when investment pricing frictions are excluded from the

FIGURE 2. Selected impulse responses to MEI shocks.



Notes. The x-axis measures the time horizon in quarters, while the y-axis represents percent deviation from the balanced growth path for consumption, investment, and the relative price of investment goods, and from steady state for hours worked.

model, as technology shocks then account for 26 percent of investment fluctuations but for only 10 percent of hours movements. As discussed in Section 5.2.2, these divergent patterns originate from the strikingly different effects of technology shocks when the model includes or excludes investment price rigidity.

Finally, the last column in Table 5 shows that shocks to good-market markups account for 60 percent of the cyclical volatility of the relative price of investment in the model, while the contribution from technology shocks is much lower at 17 percent. This decomposition is another key result of the paper, because it goes strongly against the standard assumption that supply shocks explain all, or most movements in the relative investment price. Instead, it is consistent with Beaudry, Moura, and Portier's (2015) contention that the cyclical behavior of the investment price supports a leading role for demand shocks.[9] Section 5.3 below elaborates on the economic intuition underlying this finding.

5.2.2. *Effects of technology shocks.* Using sectoral growth accounting, Basu, Fernald, Fisher, and Kimball (2013) find that improvements in consumption technology have expansionary effects on output, consumption, investment, and aggregate hours, while improvements in investment technology instead trigger generalized contractions. In turn, Basu, Fernald, and Liu (2012) argue that these comovements, at odds with both flex-price and one-sector sticky-price models, can be explained by a two-sector economy featuring nominal rigidities in both the consumption and investment markets. My estimated model provides an ideal tool to evaluate these claims in a quantitative framework.

[9]See Bouakez, Cardia, and Ruge-Murcia (2014), Gabler (2014), and Wagner (2015) for related works arguing that relative prices only weakly reflect relative technologies in multisector models.

The top four panels in Figure 3 show the estimated impulse responses of consumption, investment, aggregate hours worked, and the relative price of investment to C and I shocks. To simplify the analysis, the responses correspond to orthogonal technology innovations. This is useful to isolate the specific mechanisms through which a change in one sector's technology propagates through the economy, but of course provides little information about unconditional comovements given that the shocks are correlated.

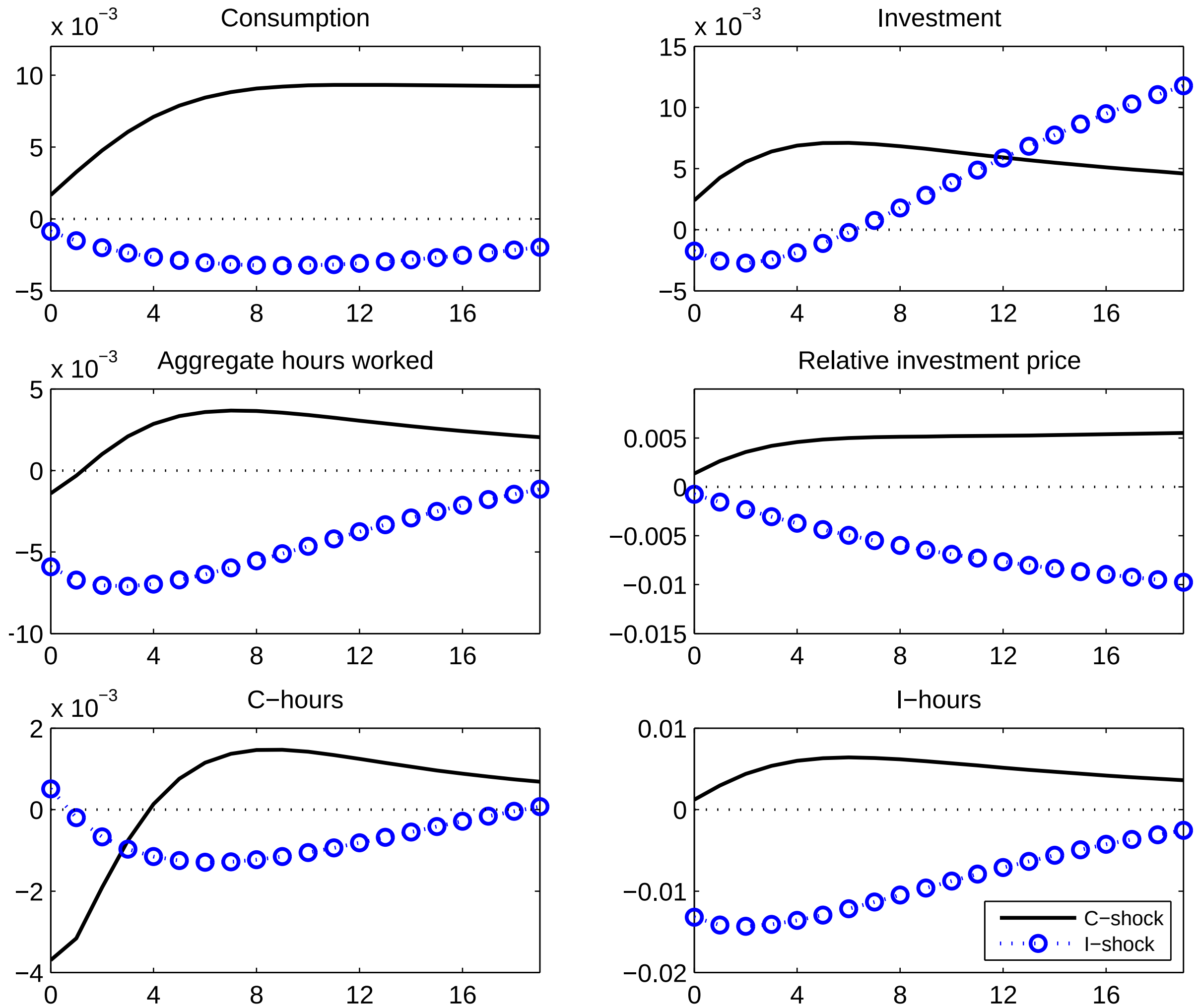
Remarkably, the estimated responses share important features with the findings in Basu, Fernald, Fisher, and Kimball (2013). Positive C shocks trigger expansions in consumption and investment, while positive I shocks push the economy into a severe recession. One difference is that aggregate hours fall on impact after a C shock in the model while they increase according to Basu, Fernald, Fisher, and Kimball's estimates, although not significantly. Strikingly, both consumption and total hours worked remain depressed for more than five years after improvements in I technology, while investment initially falls but recovers after about one year and a half. Overall, the correspondence with Basu, Fernald, Fisher, and Kimball's results, based on an unrelated empirical strategy, bolsters confidence that C and I technology shocks as well as their propagation channels have been correctly identified by the Bayesian DSGE approach.

The bottom two panels display the responses of C and I hours, clarifying the behavior of firms after technology shocks. Conditional on the movements of consumption and investment, the responses of sectoral hours are not surprising in this demand-driven economy. First, hours worked in the sector unaffected by the shock closely track the behavior of sectoral output, as illustrated by I hours after a positive C shock.[10] This is intuitive: if technology is unchanged, movements in output must be fully reflected in inputs. Second, hours in the sector affected by the shock also follow their output, but with a negative shift due to the less-than-proportional increase in demand induced by price stickiness. This is especially visible in the response of I hours to a positive I shock: although investment increases steadily after about one year and a half, I hours remain depressed at all horizons because the rise in productivity is sufficient to sustain higher production by itself.

Basu, Fernald, Fisher, and Kimball conclude from their results that C and I shocks may be a major source of fluctuations in the U.S. economy, given that they both generate business-cycle-like comovements between consumption, investment, and hours. As the variance decomposition from Table 5 shows, this contention is at odds with my estimated model, which instead favors MEI shocks. The intuition follows from the estimated

[10]On impact, the rise in C hours after the I shock seems puzzling given the simultaneous fall in consumption. It is in fact an artifact of the one-shot jump in government consumption induced by the stochastic trend.

FIGURE 3. Selected impulse responses to C and I specific technology shocks.

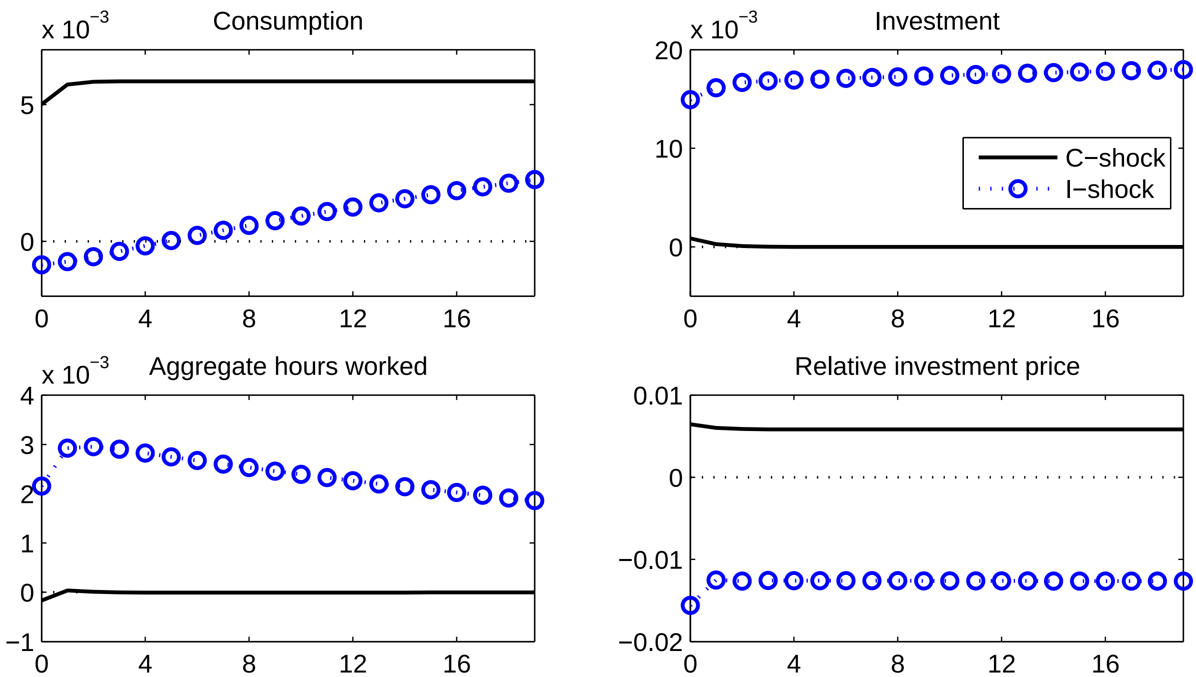


Notes. See the notes to Figure 2. The correlation between technology shocks is set to zero for the computation.

responses just discussed. In the aggregate, C shocks trigger negative short-run comovements between output and hours worked, while I shocks generate negative medium-run comovements between investment and both consumption and hours. Also, at the sectoral level both shocks induce negative comovements between C and I hours. Given these patterns, it may be premature to consider a dramatic reevaluation of the contribution of technology shocks to macro fluctuations.

From the perspective of standard models, the conditional comovements displayed in Figure 3 are puzzling. Indeed, Kimball (1994) show that shocks to consumption technology have no effect on equilibrium labor or investment in frictionless real models, while

FIGURE 4. Impulse responses to C and I shocks without nominal rigidity.



Notes. See the notes to Figure 2.

Fisher (2006) and Justiniano, Primiceri, and Tambalotti (2010) emphasize the expansionary flavor of investment supply shocks in simple two-sector models. Therefore, it is important to understand which frictions are responsible for the response patterns shown in Figure 3. Because developing analytical insights from the model is difficult, I rely instead on comparisons between the baseline specification and the restricted versions discussed in Section 5.1.

A priori, both real and nominal frictions contribute to shaping the estimated responses. However, Figure 4, which plots the responses to C and I shocks in the flexible-price, flexible-wage version of the economy, suggests that only nominal rigidities matter here. With flexible prices, technology shocks are instantaneously passed to the relative price of investment and the responses of consumption, investment, and hours worked are very different from those in Figure 3. Consistent with the argument in Kimball (1994), the C shock is fully reflected in consumption but leaves investment and hours almost unaffected, while the I shock generates a rise in investment and hours worked. Thus, real frictions alone cannot generate expansionary C shocks, and even less recessionary I shocks. In fact, it is price sluggishness in the I sector that is crucial, especially for investment-specific technology shocks to trigger a strong economic downturn. Indeed, when I prices are flexible, positive I shocks induce an immediate jump in investment and output as well as a delayed rise in hours worked. On the other hand, removing pricing frictions in the C sector leaves most of the patterns displayed in Figure 3 unchanged, suggesting that they do not constitute a key mechanism.

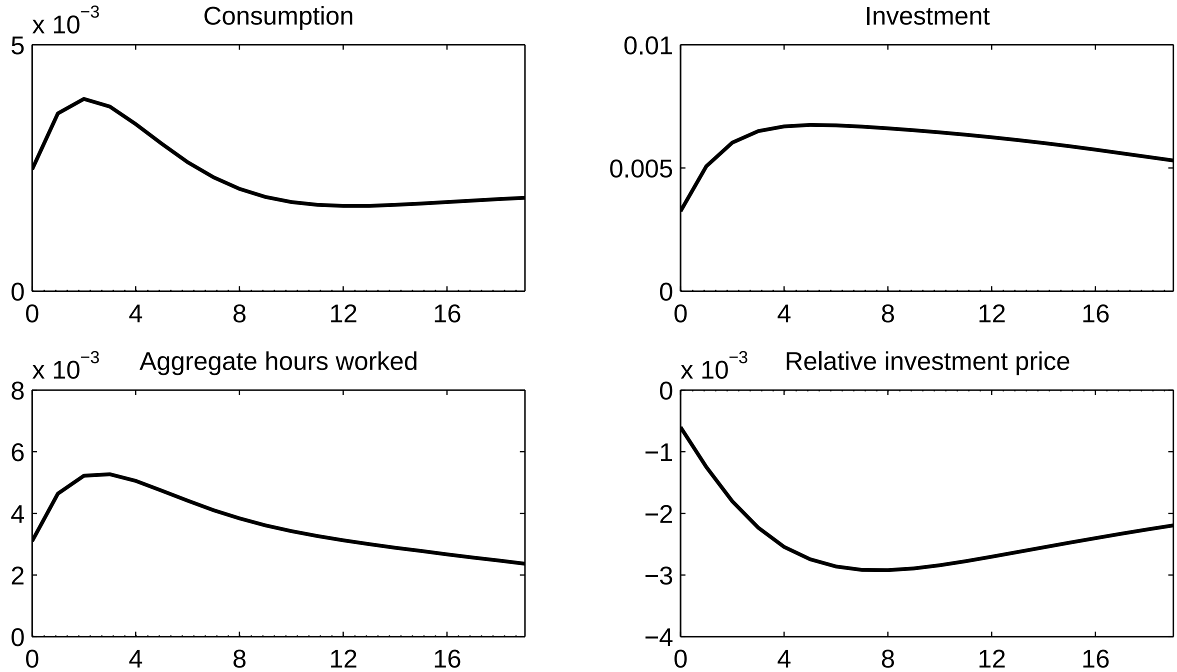
The economic logic behind these responses is developed in Basu, Fernald, and Liu (2012), building on an intuition from Barsky, House, and Kimball (2007). The key observation is that the shadow value of investment corresponds closely to the present discounted value of the stock of capital, which is quite stable over the cycle. It follows that this shadow value is relatively unresponsive to shocks, implying that households are roughly indifferent to the timing of investment purchases. Equivalently, the intertemporal elasticity of substitution is very large for investment demand. In presence of investment price rigidity, some I firms are not able to instantaneously lower their prices after a positive I technology shock, so I goods become relatively more expensive with respect to the future and this triggers a large fall in investment demand. Because hours are largely demand driven in the short run, I hours fall as well, and the corresponding reduction in household income depresses consumption. A general recession follows. In contrast, a positive C shock makes investment goods relatively cheaper today and, following a symmetric logic, generates an economy-wide expansion.

5.2.3. *Effects of monetary shocks.* In a stylized economy, Barsky, House, and Kimball (2007) demonstrate that investment price stickiness is key to the effectiveness of monetary policy: a small durable sector with rigid prices within a flex-price model can make the economy react to monetary policy as if all prices were sticky, while flexibly-priced durables may make money neutral even when consumption prices are sticky. To add some empirical content to their analysis, I briefly review the model's implications for the effects of monetary policy shocks.

Figure 5 reports selected estimated impulse responses to a monetary policy shock lowering the nominal interest rate. The shock is clearly expansionary, as consumption, investment, and aggregate hours worked all increase. At the sectoral level, C and I hours rise simultaneously. Also, the relative price of investment falls for several periods, reflecting the ability of C firms to increase their prices faster than I firms in response to the increase in demand. Overall, the economy's dynamics after a monetary shock closely resemble those from one-sector DSGE models.

In light of Barsky, House, and Kimball's analysis, it is woth investigating the relative role of consumption and investment price rigidities in shaping those dynamics. It turns out that they are equivalent mechanisms here, probably because the estimated Calvo parameters are high in both sectors. Suppressing pricing frictions in one sector while leaving them in the other has little effect on the movements displayed in Figure 5. The only noticeable changes are a fall in the persistence of the responses of consumption,

FIGURE 5. Impulse responses to an expansionary monetary policy shock.



Notes. See the notes to Figure 2.

investment, and hours worked when prices are rigid in a single sector, and a switch in the sign of the response of the relative price of investment depending on which sector is able to adjust instantaneously. On the other hand, suppressing nominal frictions in both sectors unsurprisingly makes monetary policy almost neutral.

5.3. **Shocks and the relative price of investment.** Following Greenwood, Hercowitz, and Krusell (2000), it is common to identify shocks to the relative technology between the C and I sectors using the relative price of investment. The literature essentially focuses on two practical implementations, either based on a period-by-period mapping between the two series (Justiniano, Primiceri, and Tambalotti, 2011; Schmitt-Grohe and Uribe, 2012) or on long-run restrictions (Fisher, 2006). By allowing for investment price rigidity and relaxing the standard assumption of perfect pass-through of relative technology shocks to the relative price, my model allows to compare these alternative empirical strategies.

As discussed in Section 5.2.1, C and I technology shocks account for only one fifth of the cyclical variance of the relative price of investment in the model, while the contribution of price markup shocks is above 50 percent. These respective shares reflect the large estimated Calvo coefficients. The linearized inflation equation in the consumption sector may be written as

$$\ln \pi_{c,t} - \iota_{pc} \ln \pi_{c,t-1} = \Theta_{pc} E_t \sum_{j=0}^{\infty} \left(\beta \mu^{1-\sigma}\right)^j \ln mc_{t+j}^c + E_t \sum_{j=0}^{\infty} \left(\beta \mu^{1-\sigma}\right)^j \ln \eta_{t+j}^c,$$

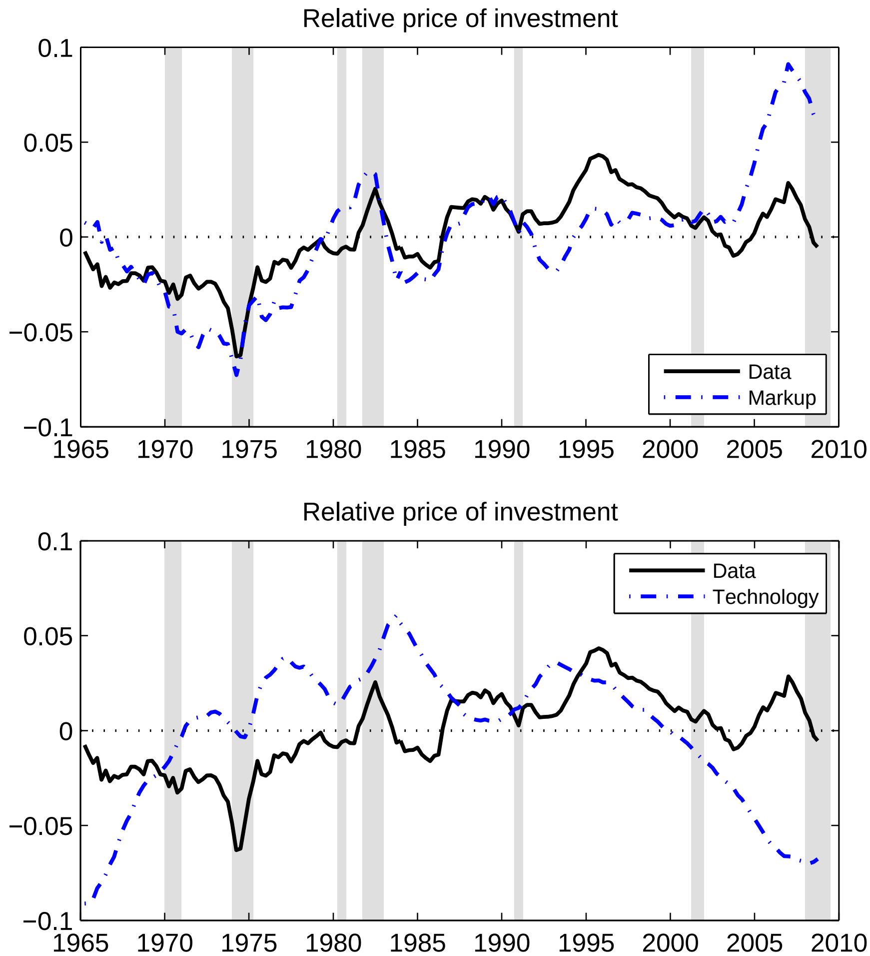
where $\Theta_{pc} = (1-\xi_{pc})(1-\beta\mu^{1-\sigma}\xi_{pc})/\xi_{pc}$ is a function of structural parameters — including the Calvo coefficient ξ_{pc} —, μ denotes the average growth rate of the economy, mc_t^c is the real marginal cost in the C sector, and η_t^c is the price markup shock in the C sector. In the aggregate, the pass-through of marginal cost shocks to the consumption price index thus depends on two statistics: the value of Θ_{pc} and the persistence of the marginal shock response. Because the estimated value of ξ_{pc} is close to unity, Θ_{pc} is close to zero and C inflation responds little to shocks shifting only the marginal cost, including technology shocks. On the other hand, the Calvo specification implies that prices react quickly to markup shocks. A similar analysis holds for investment inflation.

The slow pass-through of technology shocks to the relative price of investment is apparent in Figure 3: it takes about one year for C shocks to be fully reflected in the price and the pass-through of I shocks is even slower. Importantly, the small contribution of technology shocks in the estimated model is fully driven by the data: at the prior mean, a similar decomposition attributes 85 percent of the cyclical variance of the relative price to technology shocks, and only 2 percent to markup shocks. Therefore, it is information from the likelihood function that assigns a small weight to C and I shocks in driving price fluctuations.

Figure 6 provides a graphical representation of this decomposition. The solid line represents the actual time series for the relative price of investment, obtained by cumulating its demeaned growth rate over time. It can be interpreted as the model prediction conditional on estimated parameters, initial conditions, and smoothed shocks. On the other hand, the dashed lines correspond to the paths obtained when only markup or technology shocks are fed into the model. From the plots, it is clear that the behavior of the relative price is closely associated with markup shocks, while the contribution from technology shocks is more disconnected. In particular, most high-frequency movements in the relative price originate from markup shocks. This is reflected by simple sample statistics: the correlation between the growth rate of the relative investment price in the data and its estimated markup contribution is equal to 0.82, while it is only 0.11 with the counterfactual path driven only by technology shocks. These findings cast even more doubt on the identification approach assuming a period-by-period mapping between relative technology and the relative price of investment.

Fisher's (2006) alternative strategy is based on the long-run restriction that only relative technology shocks have permanent effects on the relative price of investment. This

FIGURE 6. Historical contributions to the relative price of investment.

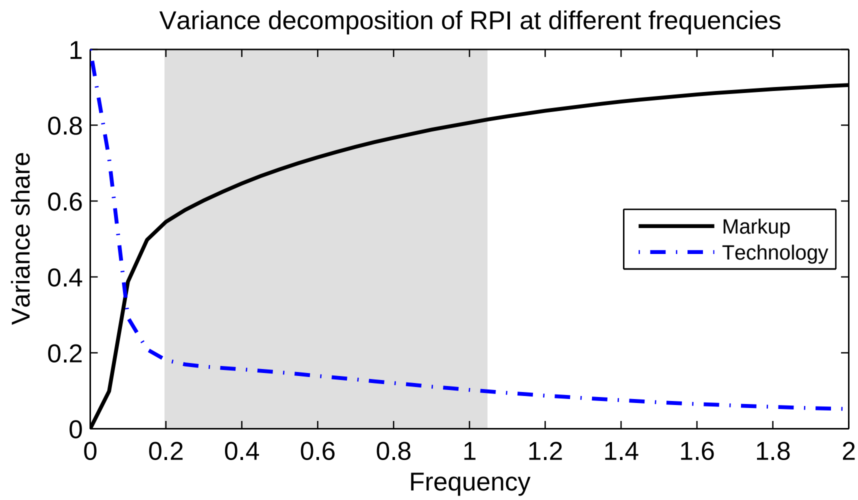


Notes. 'Markup' refers to the two price markup shocks $\epsilon^{\eta c}$ and $\epsilon^{\eta i}$, while 'Technology' refers to the C and I shocks $\epsilon^{\mu c}$ and $\epsilon^{\mu i}$. All series are detrended. Shaded bands correspond to NBER recession dates.

restriction holds in the model, as the stochastic trend driving the relative price is a composite of the two technology processes. Its empirical relevance, however, largely depends on the actual frequency band in which technology shocks are the leading contributors to the variance of the relative investment price. To take an extreme example, if technology disturbances dominate only in frequencies lower than 100 years, the long-run restriction would be of little practical use given the sample sizes typically available for macro series.

To shed light on this issue, Figure 7 plots the respective contributions of markup and technology shocks to the variance of the relative price of investment at different spectrum frequencies. The shaded band highlights the frequencies commonly associated with business cycles, corresponding to 6 to 32 quarters. Echoing the statistics in Table

FIGURE 7. Forecast error variance of the relative price of investment at different time horizons.



Notes. See the notes to Figure 6. The vertical dashed lines surround the frequencies between $2\pi/32 = 0.19$ and $2\pi/6 = 1.05$.

5, markup shocks are the leading sources of fluctuations in the relative price at business-cycle frequencies, and also at higher frequencies. On the other hand, technology shocks dominate at frequencies close to zero, reflecting the nonstationary behavior of the trend. The cutoff frequency for the lead of technology shocks is close to 63 quarters, or about 15 years. Given that available samples largely exceed such a time span, this finding provides some evidence in favor of long-run restrictions.[11]

6. CONCLUSION

This paper introduces sector-specific nominal rigidities and frictions in factor reallocation in a quantitative two-sector DSGE model. Bayesian estimation from quarterly U.S. data shows that such mechanisms are important to fit the data. In particular, I make an empirical contribution to the DSGE literature by showing the relevance of price rigidities in the investment sector, which have been mostly ignored so far.

The model sheds new light on standard macroeconomic issues. For instance, I find that technology shocks account for only one third of the movements in the relative price of investment, calling into question the validity of a widespread identification approach.

[11] Monte-Carlo experiments may help to assess the robustness of this conclusion, for instance using the estimated DSGE model as data generating process in a simulation framework similar to Erceg, Guerrieri, and Gust (2005), Christiano, Eichenbaum, and Vigfusson (2007), or Chari, Kehoe, and McGrattan (2008).

Also, consistent with the growth-accounting literature, the model predicts that improvements in consumption technology generate an expansion while improvements in investment technology trigger deep recessions. Overall, a core message of the paper is that the DSGE literature has much to gain by considering the sectoral dimension of the data, which provides both new economic mechanisms and a relevant source of identification.

In many dimensions, the model remains very stylized. Introducing labor market frictions through household preferences is clearly a shortcut for deeper mechanisms related for instance to search and matching. Also, the two-sector framework is a rough approximation of the actual structure of the U.S. economy. In particular, Beaudry, Moura, and Portier (2015) show that the empirical behavior of the relative price of investment is not homogeneous over categories of investment goods, suggesting that a three-sector model distinguishing investment in durable goods from investment in structures would be more appropriate. Finally, in the estimated model, the market value of the corporate sector is only weakly procyclical. Although this is an improvement with respect to Justiniano, Primiceri, and Tambalotti (2011), a more sophisticated description of financial markets along the lines of Christiano, Motto, and Rostagno (2014) would be required to capture the procyclical behavior of the stock market.

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Appendix A. Data and Sources

This appendix provides data sources and describes the construction of observable variables used in estimation. All quantity series are converted to per-capita terms using the population series provided by the Bureau of Economic Analysis (BEA) in its National Income and Product Accounts (NIPA, Table 2.1, line 40).

Consumption: Quantity and price series. I define nominal consumption as nominal consumption expenditures on nondurable goods and services (BEA, NIPA Table 1.1.5, lines 5 and 6). The corresponding quantity series are provided by the BEA (NIPA Table 1.1.6, lines 5 and 6). I construct the aggregate consumption quantity and price series, C_t and P_t^c, by chain aggregation.

Investment: Quantity and price series. Nominal investment is the sum of nominal consumption expenditures on durable goods and nominal fixed investment (BEA, NIPA Table 1.1.5, lines 4 and 8). The corresponding quantity series are provided by the BEA

(NIPA Table 1.1.6, lines 4 and 8). I construct the aggregate investment quantity and price series, I_t and P_t^i, by chain aggregation.

Government consumption and investment. Nominal government consumption expenditures and nominal gross government investment are provided by the BEA (NIPA Table 3.9.5, lines 2 and 3). I construct real government consumption and real government investment, G_t^c and G_t^i, by deflating each series by the corresponding chain-aggregated price index.

Hours worked. The Bureau of Labor Statistics (BLS) provides series on employment and average hours worked for the nonfarm business sector (CES0500000007), construction (CES2000000007), durable manufacturing (CES3100000007), and professional and business services (CES6000000007). For each of these sectors, I compute total hours as the product of employment and average hours.

I define investment hours, L_t^i, as the sum of hours worked in construction, durable manufacturing, and professional and business services. I include the latter sector because more than 50 percent of its output is allocated to investment according to U.S. input-output tables. The paper's findings are not sensitive to this inclusion. I then define consumption hours, L_t^c, as the difference between total hours in the nonfarm business sector and investment hours.

Wages. The BLS also provides series on nominal hourly compensation for each of the above sectors. To construct the relevant nominal wage rates, I first compute total wage bills by multiplying total hours and hourly compensation. I then split the aggregate wage bill for the nonfarm business sector between consumption and investment, using the same classification as for hours worked. Eventually, I compute the nominal consumption and investment wage series, W_t^c and W_t^i, by dividing the two sectoral wage bills by the corresponding hours series.

Inflation and the relative price of investment. Inflation in the consumption sector, π_t^c, is defined as the growth rate in the chain-aggregated consumption price index P_t^c. The relative price of investment goods, RPI_t, is defined as P_t^i/P_t^c.

Interest rate. The nominal interest rate, R_t, is measured as the quarterly average of the effective Federal Funds rate expressed in quarterly units.

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