MAGKS

Joint Discussion Paper
Series in Economics

by the Universities of

Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 13-2014

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An Empirical Analysis of Business Cycles in a New Keynesian Model with Inventories

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An Empirical Analysis of Business Cycles in a New Keynesian Model with Inventories

Marcel Förster[*,⋆]

February 18, 2014

This paper introduces inventories in an otherwise standard dynamic stochastic general equilibrium model. Firms accumulate inventories to facilitate sales, but face a cost of doing so in terms of costly storage of intermediate goods. Based on U.S. data we estimate the parameters of our model using Bayesian methods. The results show that accounting for inventory dynamics has a significant impact on parameter estimates and the following analyses. We find that inventories enter the New Keynesian Phillips curve as an additional and significant driving variable and make the inflation process less backward-looking. Moreover, impulse responses can change in terms of magnitude and persistence. The variance decomposition reveals substantial changes regarding the driving forces of inflation and the nominal interest rate when we consider inventory holding.

KEYWORDS: Inventories, Bayesian Estimation, DSGE Model, Business Cycles

JEL CLASSIFICATION: C13, E20, E30

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[⋆]For comments and suggestions, I am grateful to Peter Tillmann, Stephen Sacht, Roland Winkler, M. Ayhan Kose, Martin Mandler, Markus Jorra, Lothar Grall, Jana Brandt, and participants at the Annual Congress 2011 of the Verein für Socialpolitik, Workshop Macroeconomics and Business Cycles at ifo Dresden 2011, and DIW Macroeconometric Workshop 2011.

1 Introduction

Among the characteristic features of business cycles is the behavior of inventories. Inventory investment typically increases in boom phases and decreases in recessions. Moreover, the ratio of inventories to sales is countercyclical. This pattern has been studied in a large family of business cycle models following the work of Bils and Kahn (2000). Most of these models, however, are in the tradition of the Real Business Cycle paradigm and lack many important frictions such as nominal rigidities and monopolistic competition. The modern workhorse model for business cycle analysis, the Dynamic Stochastic General Equilibrium (DSGE) model, in contrast, is characterized by a rich set of frictions and distortions, but is often silent about inventories.

In this paper, we include inventories into an otherwise standard sticky-price business cycle model with several structural shocks such as shocks to monetary policy and technology. This allows us to explore the influence of different types of shocks on variables of interest and even more important their relevance for business cycle dynamics. For this purpose Bayesian methods are used to estimate the model parameters based on U.S. data. While the model framework is taken from the benchmark Justiniano, Primiceri, and Tambalotti (2010) model, inventory holding is modeled along the lines of Jung and Yun (2005) and Lubik and Teo (2012): storing intermediate goods facilitates sales at a given price. We depart from previous research by introducing costly storage areas needed to store the stock of inventories.

Our research focus lies on the impact of inventories, the transmission channels and how the results with inventory holding differ from previous findings in the literature, especially to those analyses that do not consider inventory holding. Since inventories allow firms to store labor services and to smooth labor demand intertemporally, results that reached a consensus among macroeconomists so far need not necessarily hold true in our setup. Against that background, we analyze whether our knowledge about the economy remains the same with inventory holding. Indeed, we find that accounting for inventories has a significant impact on the estimation results.

Our results are threefold. First, the paper presents a successfully estimated DSGE model with inventories and numerous shocks deemed important by the literature. We are able to obtain a full set of parameter estimates using Bayesian estimation techniques and examine the empirical results in a fully-specified DSGE model.

Second, the functional form of the New Keynesian Phillips Curve (NKPC) changes with inventory holding. The costs of inventory management enter the price setting problem and the marginal cost equation. As a result, inflation is not only driven by marginal costs of production, but also by the inventory-sales ratio. Moreover, when inventories are considered the degree of price indexation, i.e. our proxy for backward-looking price setting, falls significantly, thus making the Phillips curve more forward-looking.

Third, business cycle properties change when allowing for the storage of goods. Although impulse responses of the endogenous variables show the well-known pattern, they change, sometimes significantly, in terms of magnitude and persistence. Furthermore, we can analyze and distinguish between gross and fixed investment as well as output and sales. Further investigation yields that the inclusion of the inventory growth series to our data set contributes more to our results than the characteristics of the different models per se.

Several researchers have studied inventories in dynamic macroeconomic models. Jung and Yun (2005), for example, present an optimizing sticky price model that includes the accumulation of finished goods inventories. They are able to generate the observed pattern of a fall in the ratio of stocks to available goods in response to a monetary tightening. Their model, however, is estimated using a minimum distance approach to match empirical impulse response functions from a VAR in the tradition of Christiano, Eichenbaum, and Evans (2005). Another paper using the Bils and Kahn (2000) approach is the one of Lubik and Teo (2012). However, the authors stick only on NKPC resulting from their model estimated using single-equation GMM. Our approach, instead, is to confront the complete model with the data. In a similar study, Kryvtsov and Midrigan (2010) confirm the results of Jung and Yun (2005) but instead of estimating their model they perform a calibration exercise. Additionally, both studies restrict the analysis on shocks to monetary policy. Also using a calibrated model with inventories, Chang, Hornstein, and Sarte (2009) examine the reaction of employment due to permanent changes in productivity. Nevertheless, neither the effects of disturbances other than those to technology nor the behavior of inventories are considered in their analysis. Besides empirical investigations, there are numerous studies approaching this topic only theoretically. To name a few, Wen (2011) distinguishes between input and output inventories and analyzes inventory behavior, Teo (2011) analyzes business cycle in an international setup while Khan and Thomas (2007) look at inventories in an autarchy economy with an (S,s) inventory model.[1]

The existing research on inventories and business cycle models suffers from one important shortcoming: those DSGE models that explicitly account for the behavior of inventories

[1]Recently, inventories gained importance in macroeconomic research as recent studies by Den Haan (2013) in the context of goods-markets frictions, Oh and Crouzet (2013) regarding news shocks and Auernheimer and Trupkin (2014) show.

have not yet been estimated applying a system-based estimation approach to the model's entire set of shocks. A namable exception is the Bayesian estimation of a two-sector model of Iacoviello, Schiantarelli, and Schuh (2011) who distinguish between input and output inventories. However, their focus is mainly on the behavior of the firm sector and they do not consider important shocks such as shocks to capital investment and labor supply.

This paper is organized as follows. Section 2 includes inventories into an otherwise standard New Keynesian model. Details about the estimation approach and the parameter estimates are presented in Section 3 . The main results of our empirical exercise as well as a comparison with the implications of an estimated model without inventories are discussed in Section 4. Section 5 concludes.

2 A Model with Inventories

We present a standard New Keynesian model in the spirit of Smets and Wouters (2003) and Christiano, Eichenbaum, and Evans (2005) which we enhance with inventories. The modeling approach is based on Jung and Yun (2005) and Lubik and Teo (2009) who incorporate inventories into DSGE models in the manner of Bils and Kahn (2000). Storing goods boosts sales because it avoids shortages, e.g. due to unanticipated demand shifts, and market participants appreciate that their needs can be satisfied at any time. With inventories, demand can be satisfied either by current production or by the stock of goods previously produced. Firms must rent storage area if they want to transfer inventories to the next period.

In the following we present the firm sector of the model with inventories in which we distinguish between production, sales and stock of goods available. We proceed by describing the household sector and labor unions. The government sector as well as the resource constraint are presented at the end of this section.

2.1 Final Good Firms

Perfectly competitive final good firms produce the final good by purchasing differentiated intermediate goods. Goods of intermediate firms with a higher stock of available goods relative to the economy-wide average, $a_{i,t}/a_t$, are preferred. The idea is that firms with a higher level of stockkeeping have a lower probability of running out of goods and thus a final good firm faces a lower risk of not being able to compose its final good.

The Dixit-Stiglitz aggregator type function describing the technology is

$$s_t = \left[\int_0^1 \left(\frac{a_{i,t}}{a_t} \right)^{\theta \frac{\mu_t^p}{1+\mu_t^p}} (s_{i,t})^{\frac{1}{1+\mu_t^p}} \, \mathrm{d}i \right]^{1+\mu_t^p} . \tag{1}$$

Here, the variables s_t and $s_{i,t}$ denote aggregate and firm-specific sales, respectively. Cost minimization leads to the demand for the specific intermediate good

$$s_{i,t} = \left(\frac{p_{i,t}}{p_t} \right)^{-\frac{1+\mu_t^p}{\mu_t^p}} \left(\frac{a_{i,t}}{a_t} \right)^{\theta} s_t \, , \tag{2}$$

where θ is the elasticity of demand for an intermediate good of type i with respect to the stock of available goods intermediate good firm i holds in period t.

The economy-wide price index is defined as

$$p_t = \left[\int_0^1 \left(\frac{a_{i,t}}{a_t} \right)^{\theta_t} (p_{i,t})^{-\frac{1}{\mu_t^p}} \, \mathrm{d}i \right]^{-\mu_t^p} . \tag{3}$$

2.2 Intermediate Good Firms

In the monopolistically competitive intermediate goods market firms, indexed by $i \in [0,1]$, supply their specific intermediate good. Using capital, $k_{i,t-1}$, and labor services (denoted in the form of hours worked), $l_{i,t}$, the representative firm produces its output $y_{i,t}$ with the help of the technology

$$y_{i,t} = k_{i,t-1}^{\alpha} \left(z_t l_{i,t} \right)^{1-\alpha} - z_t \phi \, , \tag{4}$$

where z_t is a variable indicating the level of Labor-augmenting technological progress. It is assumed that its growth rate is stochastic. We define $v_t \equiv z_t / z_{t-1}$. The law of motion of technological progress is formulated as

$$\log v_t = (1 - \rho_v) \log v + \rho_v \log v_{t-1} + \eta_t^v \, , \tag{5}$$

and η_t^v are innovations that are IID. As it is standard in the literature, we include fixed cost of production, parameterized by ϕ. We set ϕ such that firms' profits are zero in steady state.

In period t intermediate good firms own a stock of available goods $a_{i,t}$ stemming from inventories, i.e. the stock of available goods in period $t-1$ less goods sold in period $t-1$

$(a_{i,t-1} - s_{i,t-1})$, and produced goods in period t, $y_{i,t}$. We write this as

$$a_{i,t} = y_{i,t} + (a_{i,t-1} - s_{i,t-1}) . \tag{6}$$

An identical statement is

$$x_{i,t} = y_{i,t} - s_{i,t} + x_{i,t-1} , \tag{7}$$

where $x_{i,t} = a_{i,t} - s_{i,t}$ is the stock of inventories firm i holds at the end of period t. Naturally, the inventory stock rises if the production exceeds sales and vice versa. So far, intermediate good firms have an incentive to increase the stock of available goods by raising production in order to increase sales. On the other side, firms face cost of storing inventories which lowers inventory holdings and the stock of available goods.

Every intermediate good firm has to store its stock of available goods not sold by the end of each period in order to carry it over into the next period. More precisely, the inventory stock is stored in storage areas, h_t. They are rented from households at the current rental rate r_t^h. We assume that the relation between storage areas and inventories at the end of period t is given by

$$h_{i,t} = \psi(a_{i,t} - s_{i,t}) = \psi x_{i,t} , \tag{8}$$

where ψ is a constant. As can be seen, the elasticity of storage area demand with respect to inventories is unity since we make the assumption that all goods require the same amount of storage area independent of volume and time.

The representative intermediate good firm maximizes the present discounted stream of future real profits

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \frac{\lambda_{t+\tau}}{\lambda_t} \left\{ \frac{p_{i,t+\tau}}{p_{t+\tau}} s_{i,t+\tau} - w_{t+\tau} l_{i,t+\tau} - r^k_{t+\tau} k_{i,t+\tau-1} \right.$$
$$\left. - r^h_{t+\tau-1} h_{i,t+\tau-1} - \frac{\kappa_p}{2} \left(\frac{p_{i,t+\tau}}{\pi^{\gamma_p}_{t+\tau-1} \pi^{1-\gamma_p} p_{i,t+\tau-1}} - 1 \right)^2 s_{t+\tau} \right\} , \tag{9}$$

taking into account the demand for its specific good, (2), the production technology given in (4), the evolution of the stock of available goods as defined in (6) as well as the required storage room for its inventories, (8). Labor services $l_{i,t}$ are compensated by the hourly wage rate w_t denoted in real terms, i.e. W_t/p_t, while capital is rented from households at the current rental rate r_t^k. Note that in the model with inventories revenues depend on sales $s_{i,t}$ instead of output $y_{i,t}$. At the end of each period intermediate good firms realize how much storage room they need and rent the required amount of storage areas. In the following period they settle accounts, i.e. the owners of storage areas receive payments with a lag of one period.

Prices are set according to a mechanism à la Rotemberg (1982). Each intermediate good producer decides every period about the optimal price for his specific good, taking into account that adjusting the price induces cost if the ratio between the current price and that one period before, $p_{i,t}/p_{i,t-1}$, differs from the economy-wide gross inflation rate realized one period before, i.e. $\pi_{t-1} = p_{t-1}/p_{t-2}$, and steady state inflation π. Here, γ_p is an indexation parameter. In addition, κ_p is a parameter that measures the degree of adjustment cost.

The optimal price $p_{i,t}$ satisfies the condition

$$\begin{aligned}\frac{p_{i,t}}{p_t}s_{i,t} + \mu_t^p \kappa_p \frac{p_{i,t}}{\pi_{t-1}^{\gamma_p}\pi^{1-\gamma_p}p_{i,t-1}}\left(\frac{p_{i,t}}{\pi_{t-1}^{\gamma_p}\pi^{1-\gamma_p}p_{i,t-1}} - 1\right)s_t \\ = E_t\beta\mu_t^p\frac{\lambda_{t+1}}{\lambda_t}\kappa_p\frac{p_{i,t+1}}{\pi_t^{\gamma_p}\pi^{1-\gamma_p}p_{i,t}}\left(\frac{p_{i,t+1}}{\pi_t^{\gamma_p}\pi^{1-\gamma_p}p_{i,t}} - 1\right)s_{t+1} \\ + E_t\beta\frac{\lambda_{t+1}}{\lambda_t}\left[mc_{t+1} - \psi r_t^h\right](1+\mu_t^p)s_{i,t}\,, \end{aligned} \tag{10}$$

where marginal cost mc_t are given by

$$mc_t = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}\left(r_t^k\right)^\alpha\left(\frac{w_t}{z_t}\right)^{1-\alpha}. \tag{11}$$

Without cost of price adjustment ($\kappa_p = 0$), each intermediate firm sets its price as a markup over expected marginal cost next period minus the cost of stockkeeping.

As in Justiniano and Primiceri (2008), the price markup μ_t^p is assumed to be autocorrelated of order one and driven by an exogenous IID disturbance η_t^p, formally

$$\log\mu_t^p = (1-\rho_p)\log\mu^p + \rho_p\log\mu_{t-1}^p + \eta_t^p\,. \tag{12}$$

Furthermore, optimization yields that marginal cost evolve according to

$$mc_t = \theta_t\frac{p_{i,t}}{p_t}\frac{s_{i,t}}{a_{i,t}} + E_t\left[1 - \theta_t\frac{s_{i,t}}{a_{i,t}}\right]\beta\frac{\lambda_{t+1}}{\lambda_t}\left[mc_{t+1} - \psi r_t^h\right], \tag{13}$$

Obviously, costs of stockkeeping enter both the price setting equation and the marginal cost equation. In (13), the representative intermediate good firm faces a trade-off between today's marginal cost of production plus marginal cost of inventory holding, i.e. ψr_t^h, and expected marginal cost of production tomorrow. This calculus in turn affects the choice of the optimal price in (10).

2.3 Households

The economy consists of a mass of households indexed by $j \in [0,1]$. Households purchase consumption and investment goods, supply labor and are members of labor unions which set their wages. Every household offers a specific type of labor service to intermediate good firms through labor unions. Living endlessly, each household maximizes the utility function

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[\epsilon^c_{t+\tau} \log\left(c_{t+\tau} - b c_{t+\tau-1}\right) - \frac{\left(l_{j,t+\tau}\right)^{1+\sigma_l}}{1+\sigma_l} \right], \tag{14}$$

where utility depends positively on consumption c_t and negatively on hours worked $l_{j,t}$.[2] The parameter b measures the degree of habit persistence in consumption and σ_l is the inverse of the Frisch elasticity of labor supply. We adopt a logarithmic utility in consumption in order to ensure that the steady state of the model features a balanced growth path.

Furthermore, household's preference for consumption is affected by a consumption shock ϵ^c_t with mean unity that follows

$$\log \epsilon^c_t = \rho_c \log \epsilon^c_{t-1} + \eta^c_t, \tag{15}$$

where the innovations η^c_t are IID with mean zero.

Each household faces the budget constraint

$$c_t + i^k_t + i^h_t + \frac{B_t}{p_t} = \frac{r^m_{t-1} B_{t-1}}{p_t} + \frac{W_{j,t}}{p_t} l_{j,t} + r^k_t u_t \bar{k}_{t-1} - a(u_t)\bar{k}_{t-1} + r^h_{t-1} h_{t-1} + div_{j,t}. \tag{16}$$

Here, p_t denotes the economy-wide price level. In period t, the household buys government bonds B_t which yield a return of r^m_t in period $t+1$. Finally, the nominal hourly wage rate is denoted by $W_{j,t}$ and $div_{j,t}$ captures the net flow of dividends from intermediate good firms, membership fees to labor unions and lump-sum taxes paid to the government.

Households are owner of the capital stock which they rent to intermediate good firms at the current rental rate r^k_t. Furthermore, they decide how intensively the physical capital stock is used by setting the rate of capital utilization u_t, coming at a cost of $a(u_t)$ multiplied by the stock of physical capital $\bar{k}_{t-1}$. We assume that in steady state $a(1) = 0$ as well as that $\sigma_a = a''(1)/a'(1) > 0$, with a steady state capital utilization rate of unity. By $\bar{k}_t$ we denote the

[2] Note that we exploit that in equilibrium every household chooses the same level of consumption.

end-of-period t stock of physical capital. Furthermore, $\bar{k}_{t-1}$ is related to capital k_{t-1} by

$$k_{t-1} = u_t \bar{k}_{t-1} \, . \tag{17}$$

To keep the capital stock from deteriorating the household purchases capital investment goods i^k_t. Each period, a constant share δ^k of the physical capital stock depreciates. As a result, at the end of period t the physical stock of capital is given by

$$\bar{k}_t = (1-\delta^k)\bar{k}_{t-1} + \epsilon^k_t \left(1 - S\left(\frac{i^k_t}{i^k_{t-1}}\right)\right) i^k_t \, , \tag{18}$$

where $S\left(\frac{i^k_t}{i^k_{t-1}}\right)$ are cost associated with changes in the level of investment. We assume that $S(\cdot) = S'(\cdot) = 0$ and $S''(\cdot) > 0$ in steady state. The variable ϵ^k_t is a shock to the efficiency of transforming investment goods into new physical capital, and it is assumed that it follows the stochastic process

$$\log \epsilon^k_t = \rho_k \log \epsilon^k_{t-1} + \eta^k_t \, , \tag{19}$$

with η^k_t being IID innovations.

Beside the stock of capital, households own storeage areas that they lend to intermediate good firms. For this service they earn a rent of r^h_t. Furthermore, storeage areas depreciate by $\delta^h \in (0,1)$ every period (e.g. erosion of storehouses due to environmental influences). In period t, households receive payments $r^h_{t-1} h_{t-1}$ from lending the end-of-period $t-1$ stock of storage areas to intermediate good firms.

Households can acquire storage area investment goods in order to build up the undepreciated stock of storage aras. Storage areas evolve according to

$$h_t = (1-\delta^h) h_{t-1} + \epsilon^h_t \left(1 - S\left(\frac{i^h_t}{i^h_{t-1}}\right)\right) i^h_t \, . \tag{20}$$

Similar to investments in the physical stock of capital, investing in storage areas causes adjustment cost amounting to $S\left(\frac{i^h_t}{i^h_{t-1}}\right)$ with steady state properties $S(\cdot) = S'(\cdot) = 0$ and $S''(\cdot) > 0$. In (20), ϵ^h_t is a shock to the transformation of storage area investment goods into new and rebuilt storage areas. Its law of motion is given by

$$\log \epsilon^h_t = \rho_h \log \epsilon^h_{t-1} + \eta^h_t \, . \tag{21}$$

Here, η^h_t are disturbances with IID normal distribution. A positive storage area investment shock leads to a rise in supply of storage areas. Ceteris paribus, this leads to a fall in the storage area rental rate and therefore firms face lower cost for their stored goods. Thus we refer to ϵ_t^h as an unexplained variation in the cost of inventory holding.

2.4 Labor Unions

The specific types of labor services supplied by households are bundled into one homogenous labor input, l_t. The technology used is described by the Dixit-Stiglitz function

$$l_t = \left[\int_0^1 \left(l_{j,t}\right)^{\frac{1}{1+\mu_t^w}} \, \mathrm{d}j \right]^{1+\mu_t^w} . \tag{22}$$

Cost minimization then yields that the demand for labor type j is given by

$$l_{j,t} = \left(\frac{W_{j,t}}{W_t} \right)^{-\frac{1+\mu_t^w}{\mu_t^w}} l_t \, , \tag{23}$$

where W_t is the aggregate nominal wage rate

$$W_t = \left[\int_0^1 \left(W_{j,t}\right)^{-\frac{1}{\mu_t^w}} \, \mathrm{d}j \right]^{-\mu_t^w} . \tag{24}$$

Households are members of labor unions that set the nominal wage rate and the amount of working hours. More precisely, each household is represented by exactly one labor union that corresponds to its labor type. Labor unions receive a membership fee from households to finance quadratic cost of wage adjustment. Costs depend on the growth rate of hourly wages relative to inflation and technology growth last period and in steady state. A labor union optimizes the objective function

$$E_t \sum_{\tau=0}^{\infty} \beta^\tau \Bigg\{ - \frac{\left(l_{j,t+\tau}\right)^{1+\sigma_l}}{1+\sigma_l} + \lambda_{t+\tau} \left[\frac{W_{j,t+\tau}}{p_{t+\tau}} l_{j,t+\tau} - \frac{\kappa_w}{2} \left(\frac{W_{j,t+\tau}}{\left(\pi_{t+\tau-1} v_{t+\tau-1}\right)^{\gamma_w} \left(\pi v\right)^{1-\gamma_w} W_{j,t+\tau-1}} - 1 \right)^2 \frac{W_{t+\tau}}{p_{t+\tau}} l_{t+\tau} \right] \Bigg\} , \tag{25}$$

subject to the demand for the differentiated labor service as derived in (23). In (25), λ_t is the Lagrange multiplier in the household's optimization problem associated with the budget constraint and equals marginal utility of consumption. The parameter κ_w determines the size of wage adjustment cost and γ_w is a parameter that measures the degree of indexation to past inflation and technology growth.

Finally, optimization yields the result

$$(1+\mu_t^w)\left(l_{j,t}\right)^{1+\sigma_l} + E_t \frac{\mu_t^w \beta \kappa_w \lambda_{t+1} W_{j,t+1}}{\left(\pi_t v_t\right)^{\gamma_w}\left(\pi v\right)^{1-\gamma_w} W_{j,t}} \left(\frac{W_{j,t+1}}{\left(\pi_t v_t\right)^{\gamma_w}\left(\pi v\right)^{1-\gamma_w} W_{j,t}} - 1\right) \frac{W_{t+1}}{p_{t+1}} l_{t+1}$$
$$= \lambda_t \frac{W_{j,t}}{p_t} l_{j,t} + \frac{\mu_t^w \kappa_w \lambda_t W_{j,t}}{\left(\pi_{t-1} v_{t-1}\right)^{\gamma_w}\left(\pi v\right)^{1-\gamma_w} W_{j,t-1}} \left(\frac{W_{j,t}}{\left(\pi_{t-1} v_{t-1}\right)^{\gamma_w}\left(\pi v\right)^{1-\gamma_w} W_{j,t-1}} - 1\right) \frac{W_t}{p_t} l_t \,. \quad (26)$$

Without adjustment cost, the real wage multiplied by marginal utility of consumption would be a markup over the disutility of work. The markup μ_t^w evolves according to

$$\log \mu_t^w = (1-\rho_w)\log \mu^w + \rho_w \log \mu_{t-1}^w + \eta_t^w \,, \quad (27)$$

whereas η_t^w are the IID innovations.[3]

2.5 Government and Market Clearing

The monetary authority sets the nominal interest rate r_t^m according to a generalized Taylor rule. More precisely, monetary policy is described by the formula

$$\frac{r_t^m}{r^m} = \left(\frac{r_{t-1}^m}{r^m}\right)^{\rho_m} \left[\left(\frac{\pi_{t-1}}{\pi}\right)^{\varphi_\pi} \left(\frac{y_{t-1}}{z_{t-1} y^*}\right)^{\varphi_y}\right]^{1-\rho_m} \left(\frac{\pi_t}{\pi_{t-1}}\right)^{\varphi_{\Delta\pi}} \left(\frac{y_t}{v_t y_{t-1}}\right)^{\varphi_{\Delta y}} e^{\eta_t^m} \,. \quad (28)$$

Note that y^* is the steady state value of stationarized output. In linearized terms, (28) becomes

$$\widehat{r}_t^m = \rho_m \widehat{r}_{t-1}^m + (1-\rho_m)\left(\varphi_\pi \widehat{\pi}_{t-1} + \varphi_y \widehat{y}_{t-1}^*\right) + \varphi_{\Delta\pi}(\widehat{\pi}_t - \widehat{\pi}_{t-1}) + \varphi_{\Delta y}(\widehat{y}_t^* - \widehat{y}_{t-1}^*) + \eta_t^m \,, \quad (29)$$

where y_t^* is the stationarized output level. A hat above a variable denotes its percentage deviation from steady state. We add an IID shock η_t^m to the interest rule to allow the actual federal funds rate to deviate from the formulated Taylor rule.

Furthermore, we assume that the ratio of government spending, g_t, to final sales varies over time depending on an exogenous shock to governmental economic activity, i.e.

$$g_t = \left(1 - \frac{1}{\epsilon_t^g}\right) y_t \,. \quad (30)$$

[3] As for the model in Justiniano, Primiceri, and Tambalotti (2010), in our linearized model the wage markup shock has the same effect as a shock that would affect household's disutility of labor in (14). Including such a 'labor supply' shock would also require a decision between an autocorrelated and an IID shock, since two autocorrelated shocks in the wage setting equation bring up identification issues. Therefore we omit the labor supply shock.

where the evolution of the government spending shock ϵ_t^g is given by (letting η_t^g be IID disturbances)

$$\log \epsilon_t^g = (1-\rho_g) \log \epsilon^g + \rho_g \log \epsilon_{t-1}^g + \eta_t^g \,. \tag{31}$$

With inventories and storage specific investment goods that accompany the existence of storage areas the aggregate resource constraint becomes

$$c_t + i_t^k + i_t^h + g_t + a(u_t)\bar{k}_{t-1} + \frac{\kappa_p}{2}\left(\frac{\pi_t}{\pi_{t-1}^{\gamma_p}\pi^{1-\gamma_p}} - 1\right)^2 s_t = s_t \,. \tag{32}$$

In this economy total investment, i_t, is the sum of the two specific investment goods, i.e. $i_t = i_t^k + i_t^h$.

3 Estimation

3.1 Bayesian Approach

In recent years Bayesian estimation of DSGE models has become popular for various reasons. It is a system-based estimation approach that offers the advantage of incorporating assumptions about the parameters, coming from either economic theory or previous micro- and macroeconomic studies. The assumptions can be nested comfortably in the econometric framework and reduce weak identification issues as well.

Bayesian estimation is based on Bayes' theorem. It states that the posterior distribution of the parameters can be computed from the likelihood function and the prior distribution. The prior distribution has to be specified by the researcher and reflects her beliefs about the true parameter values.

Let $p(\zeta)$ be the prior distribution and $p(\zeta|Y_t)$ be the posterior distribution of our model's parameter set, say ζ. By Y_t we denote the data set. Then, Bayes' theorem states that

$$p(\zeta|Y_t) = \frac{p(Y_t|\zeta)\, p(\zeta)}{p(Y_t)} \,, \tag{33}$$

where

$$p(Y_t) = \int p(Y_t|\zeta)\, p(\zeta)\, \mathrm{d}\zeta \tag{34}$$

is the marginal likelihood of the data conditional on the model. The marginal likelihood is a constant and therefore it plays no role for the maximization of the posterior. Thus, we can disregard the marginal likelihood and obtain the proportional term

$$p(\zeta|Y_t) \propto p(Y_t|\zeta)\, p(\zeta)\,. \tag{35}$$

Furthermore, it is well-known that the probability of the data given the parameters is equivalent to the likelihood function of ζ given Y_t, or formally: $p(Y_t|\zeta) \equiv \mathcal{L}(\zeta|Y_t)$. As a result, we obtain the formula

$$p(\zeta|Y_t) \propto \mathcal{L}(\zeta|Y_t)\, p(\zeta) \tag{36}$$

We build up the likelihood function with the help of filter techniques. First, the models' equilibrium conditions are log-linearized around the non-stochastic balanced growth path. When applicable, we detrend the variables by the current level of technology in order to make them stationary. Using a generalized Schur decomposition the system of equations is then transformed into its state space form where the observed (control) variables are linked to the predetermined (state) variables. Given the state space representation of our model, the Kalman filter is applied to generate optimal forecasts of and inference about the vector of unobserved state variables. With the results obtained by the Kalman algorithm we are able to evaluate the joint likelihood function of the observable endogenous variables.

The posterior distribution of the parameters, $p(\zeta|Y_t)$, is derived as follows: First, we numerically optimize (36) in logarithmic terms so as to obtain a maximum, called the posterior mode, and approximate standard errors, the latter based on the inverse Hessian evaluated at the posterior mode. Thereafter, the parameter values of the posterior mode as well as the Hessian are employed to simulate the posterior distribution which is derived numerically by applying Monte-Carlo Markov-Chains methods. In this way we can generate draws of the parameters in ζ, the realisations of which yielding the posterior distribution of ζ (according to (33) and (34)). As in most applications of Bayesian estimation with respect to DSGE models, we employ the Random-Walk Metropolis-Hastings algorithm.[4]

We estimate the model by running two chains of the Random-Walk Metropolis-Hastings algorithm with 200,000 iterations in each case. This is sufficient to let the algorithm converge. We drop the first 75,000 candidates and retain every 25th draw. Finally we keep 10,000 draws from which we calculate the posterior distribution of the parameters, the variance decompositions and the impulse responses. Autocorrelation and cross-correlation functions are obtained

[4]The Random-Walk Metropolis-Hastings algorithm was first used by Schorfheide (2000) and Otrok (2001), later in common articles such as Smets and Wouters (2003) as well as Adolfson, Laseen, Linde, and Villani (2007), amongst others.

by generating 200 observations. This is done 100 times for each of the 500 parameter draws taken from the total of 10,000 draws.

3.2 Data and Priors

We employ quarterly U.S. data on real consumption, real investment, real compensation per hour, and real GDP, obtained by dividing nominal terms by the price index. The price index is calculated by the ratio of nominal to real GDP. Expenditures for durable consumption goods are attributed to investment expenditures. Furthermore, data on hours worked in nonfarm business sector, the federal funds rate and nonfarm inventories to final sales are used for estimation. When applicable we divide the mentioned time series by civilian noninstitutional population aged over 16.[5] The time series on hours worked is normalized such that its sample average is zero. Similar to Smets and Wouters (2007), our sample starts in 1957Q1, but we use observations up to 2006Q4. The first 10 years we use for the initialization of the Kalman Filter. We decide to stop in 2006 in order to not let financial activity and financial shocks, as it was the case in the recent financial crisis, distort our estimates, especially regarding the shock processes. As we focus on the relevance of capital investment shocks under inventory adjustments, among other investigations, excluding this period of large economic distress seems justified.

Several parameters are fixed during estimation. The depreciation parameters δ^h and δ^k are both set to 0.025, implying a depreciation of 10% at annual rate. We set α to 0.3. Furthermore, we choose a value of 0.2 for the steady state wage markup μ^w. Due to the assumption of adjustment cost à la Rotemberg (1982) we have to fix either μ^w or the adjustment cost parameter κ_w in order to ensure identification. The steady state ratios of consumption, investment and government spending to sales are set to 0.55, 0.25 and 0.2, respectively. The ratio of inventories to output in steady state, x/y, is fixed to 0.66.These values correspond to the average values in our sample.

Table 1 shows the prior distributions for the estimated parameters. In the following we shortly comment our prior choice and name the corresponding studies. For a more extensive discussion the reader is refered to the mentioned literature.

The priors for υ, π, S'', ρ_m are taken from Smets and Wouters (2007). In addition, the autoregressive coefficients and standard deviations of shocks are similar to the ones in Smets and Wouters (2007), but with a standard deviation of unity for the shocks. The prior for

[5] Except for the inventories-to-sales ratio, which is extracted from NIPA tables of the Bureau of Economic Analysis, all data are taken from the FRED Database.

habit consumption, b, captures the range of results in the business cycle literature (Justiniano, Primiceri, and Tambalotti (2010) and Smets and Wouters (2007)) as well as of the results of micro studies (e.g. Ravina (2007)). The discount rate β as well as the parameters regarding indexation, γ_w and γ_p, resemble the priors in Justiniano, Primiceri, and Tambalotti (2010) and Smets and Wouters (2007). As in Smets and Wouters (2007), hours worked in steady state, l_{stst}, are distributed normally around zero. The prior for the inverse Frisch elasticity, σ_l, is taken from Justiniano, Primiceri, and Tambalotti (2010). Our prior for σ_a (elasticity of capital utilization) is less strict than the one formulated in Justiniano, Primiceri, and Tambalotti (2010). For the adjustment cost parameters, κ_p and κ_w, we adopt the priors from Gerali, Neri, Sessa, and Signoretti (2010). The Taylor rule parameters have priors similar to Smets and Wouters (2007) (φ_π) and Adolfson, Laseen, Linde, and Villani (2007) (φ_y, $\varphi_{\Delta\pi}$, $\varphi_{\Delta y}$).

The prior for the elasticity of demand with regard to available goods, θ, is set to an intermediate value of the results in Jung and Yun (2005). With a mean of 0.6 and a standard deviation of 0.2 (normally distributed), 95% of the prior density lies between 0.2 and 1. Concerning the ratio of storage areas to inventories, ψ, we choose as prior a beta distribution with mean 0.4 and standard deviation of 0.2.

3.3 Posteriors

The estimated parameter results are shown in Table 1. Technology growth in steady state is estimated to be 0.32 which is considerably smaller than assumed while steady state quarterly inflation is somewhat higher with a value of 0.69. Our estimate for the consumption habit parameter, a median value of 0.79, confirms the estimates in Justiniano, Primiceri, and Tambalotti (2010), where it also seems to be more relevant than found in Smets and Wouters (2007).

The result for the inverse Frisch elasticity corresponds mainly to the prior and is similar to the one estimated in Smets and Wouters (2007) (0.91 to 2.78). French (2004) examines the response of labor supply to changes in wages during 1980 to 1986 and reveals values between -0.5 and 0.6 for the Frisch elasticity, meaning a value of 1.7 or higher for the inverse as our results confirm.

The results obtained for costs of changes in capital utilization fit almost perfectly the findings presented in Justiniano, Primiceri, and Tambalotti (2010). Price and wage adjustment cost are slightly higher than expected, indicating a non-negligible degree of price and wage stickiness. On the other side, we obtain low indexation to past inflation (and technology growth regarding wage changes) which corresponds to a stronger forward-looking component in the Phillips curve.

Turning to the parameters regarding inventories we see that the demand elasticity of sales with respect to available goods, θ, is estimated to be around 0.3, a value that is in accordance with the lower estimates in Jung and Yun (2005). Rather the trade-off between cost of production and storing goods than a demand effect determines the amount of available goods in each period. Finally, the steady state price markup estimate implies a high degree of firm market power (median markup of 62%) and it is significantly higher than the formulated prior.

With dynamic costs of stockkeeping, inventories and sales are part of the NKPC. More precisely, in linearized terms the inflation equation in our model is

$$\begin{aligned}\widehat{\pi}_t = &\underbrace{\frac{\beta}{1+\beta\gamma_p}}_{0.8580} E_t\widehat{\pi}_{t+1} + \underbrace{\frac{\gamma_p}{1+\beta\gamma_p}}_{0.1401}\widehat{\pi}_{t-1} + \widehat{\widetilde{\mu}}_t^p \\ &+ \underbrace{\frac{1+\frac{1}{v}\frac{x}{y}+\mu^p\theta\left(1-\frac{v-1}{v}\frac{x}{y}\right)}{\left(1+\frac{1}{v}\frac{x}{y}-\theta\left(1-\frac{v-1}{v}\frac{x}{y}\right)\right)\mu^p\kappa_p\left(1+\beta\gamma_p\right)}}_{0.0336}\left[\widehat{mc}_t + \underbrace{\frac{\mu^p\theta\left(1-\frac{v-1}{v}\frac{x}{y}\right)\left(1-\frac{1-\frac{v-1}{v}\frac{x}{y}}{1+\frac{1}{v}\frac{x}{y}}\right)}{1+\frac{1}{v}\frac{x}{y}+\mu^p\theta\left(1-\frac{v-1}{v}\frac{x}{y}\right)}}_{0.0402}(\widehat{x}_t-\widehat{s}_t)\right],\end{aligned} \tag{37}$$

where we normalize the markup shock such that $\widehat{\widetilde{\mu}}_t^p = \frac{1}{(1+\mu^p)\kappa_p(1+\beta\gamma_p)}\widehat{\mu}_t^p$. The values assigned to the coefficients are medians calculated from the retained 10,000 parameter draws.

The elasticity of current inflation with respect to contemporaneous marginal exceeds 3%. This estimated value lies at the far upper end of results of estimated DSGE models. While several studies obtained point estimates around 2% (e.g. Smets and Wouters (2007)), 2.5% (e.g. Justiniano, Primiceri, and Tambalotti (2010)) or nearly 3% (e.g. Gertler, Sala, and Trigari (2008)), most estimation results are centered around 1% (see for example Altig, Christiano, Eichenbaum, and Lindé (2011) or Adolfson, Laseen, Linde, and Villani (2007)). Overall, marginal cost affect current inflation quite considerably (compared to the literature) and we estimate a stronger forward-looking component than generally observed.

The ratio of inventories to sales have an influence on current inflation that is only 4% of the one of marginal cost coefficient. Note that current marginal cost and inventories are related to future marginal cost by (13) which in turn affects (expected) future inflation. Using a single-equation GMM approach Lubik and Teo (2012) estimate values of 5.85% and 4.03% for the elasticity of current inflation with respect to marginal costs, depending on the calculation method of the marginal cost series. Their corresponding estimate for the sales and available goods coefficient corresponding to our notation is 1%. Notably, a significant difference is that the results of Lubik and Teo (2012) depend on the assumption that marginal cost consist solely of the wage rate. Furthermore, our inflation equation with inventories is more forward-looking: Lubik and Teo (2012) obtain an elasticity of current inflation with respect to expected future inflation of less than 80% and of about 20% regarding past inflation. With their inventory model estimated by impulse response matching Jung and Yun (2005) obtain a coefficient in front of marginal cost that is below 0.3% and changes in past or future inflation feed into a change of current inflation by 50%.

Concluding, our estimates for the elasticities of current inflation to marginal cost and the ratio of inventories to sales take values in the upper range of previous results of above mentioned studies. For this reason and a low indexation parameter inflation is comparatively flexible and it should react relatively strongly to changes in marginal cost, the inventory-sales ratio and expected inflation for tomorrow.

4 Empirical Results

4.1 Empirical Fit

To examine the empirical fit of our model, we first discuss the cross-correlations between the endogenous variables as predicted by our model. Figure 1 presents the results for selected variables. Overall the model captures the empirical correlations quite well, i.e. the empirical correlations lie mostly within the 90% confidence band. For inventory growth we obtain quite reasonable results, albeit the model shows a too large persistence. Nevertheless, the correlations mostly coincident with exceptions regarding output and gross investment growth where the model has difficulties to match the empirical counterparts.

Similar to Justiniano, Primiceri, and Tambalotti (2010), our model cannot claim to replicate the cross-correlation pattern between consumption growth and investment growth correctly. This does not hold for the output growth and gross investment growth series where observed and fitted cross-correlations are almost identical. Summing up, we can state that our model can compete with other models previously presented in the literature and does a good job in replicating the correlation structure of the inventory growth series.

4.2 Impulse Responses

In Figure 2 we display the response to a technology shock. Most variables increase significantly from the very beginning. Hours worked decrease initially but rise significantly above their steady state value after two periods. This is in line with findings in Gertler, Sala, and Trigari (2008) who estimate a labor-market search model without inventories. The stock of inventories increases gradually while the ratio of inventories to output shrinks significantly over all time horizons. Note that this result coincides with the observed pattern of procyclical inventories and a countercyclical inventories-sales ratio.

The price markup shock (depicted in Figure 3) leads to a fall in output and even more in sales, thus inventories rise. Capital investment declines stronger than fixed investment which in turn falls more than gross investment. Higher labor supply combined with a fall in labor demand leads to a reduction in the real wage by more than 1% compared to its steady state level. As for the technology shock, inventories rise gradually.

We now turn to the shocks that are associated with households' behavior. The responses to a wage markup shock are shown in Figure 4. It can be seen that inflation rises significantly while output and sales fall. The reactions of investments differ, albeit only slightly. Inventories decline significantly and persistently. In the short run a rise in the inventories-output ratio can be observed. The ratio declines in the long run as a result of a constant fall in the stock of inventories that outweighs the fall in demand.

The impulse responses to a positive capital investment shock (shown in Figure 5) are similar to those in Justiniano, Primiceri, and Tambalotti (2010) with one exception: the response of capital investment is of lower magnitude, our inventory model predicts an even more reluctant responses in comparison for fixed and gross investments. The more effective transformation of capital investment goods into new capital increases demand for investment goods and total demand. Higher output leads to higher labor demand, resulting in an increase in the real wage per hour. Sales react somewhat stronger than output and inventories are significantly below their steady state value for about four years.

Several dynamic models have been developed to study the effects of monetary policy on inventories, e.g. Jung and Yun (2005) and Kryvtsov and Midrigan (2010). Figure 6 presents the responses of the variables to a positive shock to the nominal interest rate. As in Jung and Yun (2005) who employ a minimum distance approach for their estimation, output, inflation and the sales-to-available goods ratio fall significantly (i.e. the ratio of inventories to sales rises significantly).[6] Beyond that, their model with habit consumption and quadratic adjustment costs related to the sales-to-available goods ratio delivers almost identical responses in terms of magnitude and persistence. Contrary to this result, Kryvtsov and Midrigan (2010) find that the ratio of inventories to sales remains nearly unchanged given a small depreciation of the inventory stock and adjustment cost in output deviations from steady state. Regarding hours worked and the hourly real wage rate we obtain a significant negative deviation as in Gertler, Sala, and Trigari (2008).

4.3 Variance Decomposition

The contribution of the structural shocks to the forecast error variances of selected variables is shown in Table 3 to Table 5. As in Justiniano, Primiceri, and Tambalotti (2010), capital investment shocks are important for short-term fluctuations in output, although the effect is not as strong as in the authors' study. Sales are more exposed to capital investment shocks in the short-run than production. While storage investment shocks are negligible for the variance of sales, for output they are, but in the very short-run only. Our results support the strong responsibility of technology shocks for output variations as typically found in the literature for both output levels (e.g. in Smets and Wouters (2005)) and growth rates (e.g. in Gertler, Sala, and Trigari (2008)), particularly in the long run. Moreover, our inventory model claims that shocks to technology are by far the major source for movements in output and sales, capital investment shocks and storage area investment shocks matter only in the short run.

For inventories, shocks to the cost of inventory holding explain almost entirely the variations. Only after 10 years wage markup shocks become significant, as they affect marginal cost and thus the intertemporal substitution of production. The ratio of inventories to output is more prone to investment shocks, i.e. capital investment (within the first ten quarters) and storage investment (from less than one year on). Interestingly, price markups matter more than for inventories and output alone.

Turning to Table 4, we see that capital investment shocks are the most important source for fluctuations in the different investment types. Only in the long run technology shocks contribute significantly to the variations. Remarkably, capital investment shocks lose importance with higher aggregation levels while technology shocks explain a larger fraction of the vari-

[6] Linearized the inventories-to-sales ratio and the ratio of sales to available goods are related via the formula

$$\widehat{s}_t - \widehat{a}_t = -\left(1 - \frac{s}{a}\right)\left(\widehat{x}_t - \widehat{s}_t\right) .$$

ances. Interestingly, gross investment is the only kind of investment that is affected by shocks to storage investment. Fixed investment, i.e. the sum of investments in capital and storage areas, is completely unaffected to storage shocks. Remarkably, gross investment, i.e. fixed investment plus changes in inventories, is exposed to shocks to storage area investment within the first year. This proves that shocks to storage area investment can be interpreted as shocks to the cost of inventory holding since they lead to inventory adjustments while leaving fixed investments untouched, i.e. no demand effect. Consumption is only driven by consumption shocks, short-term, and by technology shocks constantly.

In the next step we take a look at the labor market, Table 5. Wage markup shocks hit the real wage temporarily while technology shocks and shocks to the price markup have a very persistence effect. Other shocks are negligible. Interestingly, the fluctuations in hours worked are due to a different set of shocks. In contrast to the real wage, wage markup shocks contribute substantially after a year. In the short and medium run, investment shocks matter.

Policy makers concerned about inflation should focus on mark up shocks only. Both shocks are responsible for more than 75% of the forecast error variance. The nominal interest rate was historically adjusted according to capital investment socks and wage markup shocks, both having a direct effect on marginal cost. The importance of monetary policy shocks in the short run could display the lag of monetary policy reaction to shocks, maybe due to a lack of real-time data when decisions must be made. Surprisingly, governmental shocks do not matter for the movements in macroeconomic variables, neither public spending nor interest rate adjustments.

4.4 Assessing the Effect of Inventory Holding

In this section we discuss the gain from our inventory model in comparison to a standard New Keynesian model with inventories. First of all, we are interested in the changes and improvements in light of both a larger model and possible misspecification. Furthermore, note that the addition of the inventory growth series to the data set can be cumbersome. Kryvtsov and Midrigan (2010) discuss this problem in the context of estimating the model in Smets and Wouters (2007) with inventories. Nevertheless, our model could be brought to the data and in order to examine whether inventories and the inclusion of the time series inventory growth have an effect on the transmission of shocks we estimate a model without inventories.[7]

[7] The model without inventories is very similar to the one in Justiniano, Primiceri, and Tambalotti (2010).

The parameter estimates are shown in Table 2. For the baseline model without inventories, we obtain a significant lower estimate for the investment adjustment cost parameter. With a median value of 1.16 this parameter is quite low with regard to other results in the literature.[8] A high discrepancy is revealed regarding the elasticity of capital utilization cost parameter. With a median value of 7.85 in the baseline model this parameter is estimated to be surprisingly high.

The price and wage adjustment cost parameters are both lower but for wages the difference is substantial. The difference in the specifications of the elasticities of current inflation with respect to current marginal cost in the New Keynesian Phillips Curve reveal that the price adjustment cost parameter has to take a higher value, i.e. to adjust, in the inventory model. For wages we suggest that the significant higher estimated value for the inventory model is a result of the discrimination between output and sales and the feasibility of more volatile marginal cost that the model tries to match with the data. Assigned to the indexation parameters are values above the ones estimated for the inventory model, which means that in the model with inventories inflation and wages are more strongly driven by expected future values than past realizations.

Regarding the standard deviations of the structural shocks, the evidence is mixed. For example, we have significantly larger wage markup shocks in the non-inventory model, i.e. higher standard deviations, while capital investment shocks are estimated to be of larger size with inventories. The significant higher standard deviation of the price markup shock indicates that inflation can be explained more explicitly when we consider inventories. Note that all autocorrelation coefficients remain unchanged except the ones for the technology shock and capital investment shock, both decrease with inventories modelled.

The autocorrelations and cross-correlations are plotted in Figure 1 (dashed gray lines). Pertaining to the shortcoming regarding the cross-correlations between consumption and investment discussed before we see that the model without inventories even does worse, albeit the models' cross-correlations are not significantly different. Without inventories, the estimated model seems to mimic the autocorrelation of several variables slightly better. But again, the results do not significantly change when we banish inventories. Taking all together, the inclusion of inventories leads to a better fit in terms of correlations. In almost all cases the obtained results of the model with inventories better match the empirical counterparts.

[8] As an example, see Gertler, Sala, and Trigari (2008) and Justiniano, Primiceri, and Tambalotti (2010) who use the same formulation of investment adjustment cost. Adolfson, Laseen, Linde, and Villani (2007) and Sahuc and Smets (2008) even obtain estimates significantly higher than the median estimate of 3.23 for our inventory model.

Figure 2 to Figure 6 show the impulse responses of the non-inventory model (dashed gray lines). Most striking is the changing response of inflation to most of the shocks. These results can be attributed to the corresponding changes in marginal cost only in half of the cases. The wage markup and capital investment shock lead to a lower reaction of marginal cost in the non-inventory model that goes along with a higher inflation response (in comparison to the inventory model). Note that the inventories-to-sales ratio affects production and therefore marginal cost, both determining the price setting decision. Overall, the impulse responses of the model without inventories are significantly different for at least some of the variables displayed. Besides the inflation series, the greatest deviations are for the investment and policy rate series.

Are the differences in impulse responses caused by the models' equilibrium conditions or by the parameter estimates? To answer this question we take the parameter vector of the model with inventories at the posterior mode and use it to simulate the non-inventory model. The results for selected shocks and variables are presented in Figure 7 to Figure 11. It is eye-catching that the impulse responses do not significantly change for both models when the parameters are identical. In some cases the variables would even respond more strongly in the counterfactual case, but the parameter estimates lead to damped reaction in the end.

In a next step we want to shed some light on what causes the different parameter estimates that lead to divergent responses for both estimated models. For this purpose we estimate the model with inventories again but leave out the time series for the inventory growth. Impulse responses are depicted in Figure 12 to Figure 16. If the data for inventory growth implies some odd behavior the model tries to match, we would expect very to see impulse responses that are considerably different from the results of the complete data set estimation. And indeed, the responses deviate significantly in most cases. Only for technology shocks we obtain the same results since the responses are quite robust to different specifications and parameter estimates. But our figures do not show a rapprochement towards the non-inventory results. In some cases we see even larger differences between both types of models than in our benchmark estimation. Thus, inventory growth as additional time series used for estimation yields a large discrepancy regarding impulse responses, meaning that it contains additional information compared to other time series frequently used for DSGE model estimation.

However, misspecification could have led to biased estimation results in both models. Since DSGE models are stylized models they will never coincide with the true data generating process. As a result, misspecification will always be present and will affect parameter estimates as well as statistical inference. Moreover, the choice of observable variables in the estimation, i.e. the use of the inventory growth series as additional observation in the inventory model, influences the parameter estimates and, as a matter of course, the empirical results.

The analysis of the variance decomposition for the model without inventories, shown in Table 6, reveals that for inflation and the monetary policy instrument it makes a difference whether we consider inventories. Without inventory holding, capital investment shocks are responsible for about two thirds of the forecast error variance in the nominal interest rate. With inventories, the size is less than one third. Markup shocks also become more important with inventories, whereas shocks to wages are the second major source of fluctuations in the medium and long run.

A similar picture we obtain for the inflation rate. While markup and investment shocks drive inflation in the classical model, both markups shocks are far more relevant with inventories. The capital investment shocks instead is not of interest when it comes to inflation movements. For other variables of interest, the changes are only small and do not change substantially. The differences in impulse responses are proportional to some extent and yield a equivalent composition it seems.

5 Conclusion

We presented a New Keynesian DSGE model with inventories estimated using a Bayesian approach. Analogous to Bils and Kahn (2000), firms face an increase in demand when they enlarge their stock of available goods relative to the economy-wide average. As a result, output and sales can temporarily differ and firms face a trade-off between cost of production and cost of storing goods. The inventory model does a good job in terms of autocorrelations and cross-correlations with regard to the endogenous variables and the inventory growth series. It reveals significant differences with regard to impulse responses in comparison to a standard model without inventories. Regarding the variance decompositions we obtain a differentiated picture.

Several impulse responses change significantly in terms of magnitude and persistence when we add inventories to an otherwise standard New Keynesian model. While many reactions lie within the confidence bands produced by the inventory model, inflation and the nominal interest rate deviate significantly. Only in half of the cases these observations can be assigned to different behavior of marginal cost. Depending on the shocks, we also observe substantial differences between the two models. The differentiation between various categories of investment per se does not matter, it seems. Rather the fact that investment consists of more components than capital leads to the possibility to let the model adjust the variables in a different manner.

A decomposition of the forecast error variances underlines the strong effect of technology shocks on variations in output that is typically found in the literature, especially in the long run. Shocks to storage area investment lead to changes in inventory investment while leaving fixed investments untouched, thus they can be judged inventory cost shocks since the demand effect is negligible. Especially this type of shock is responsible for output variations in the very short run and continuously for deviations of inventories from steady state. Surprisingly, governmental shocks do not matter for the movements in macroeconomic variables, neither public spending nor interest rate adjustments.

In general, the results obtained do not differ due to the model properties and transmission channels. Rather a change in parameter estimates is the main driver for the changes. Our analysis reveals that the augmentation of the standard set of variables on which DSGE models are typically estimated by the inventory growth series is a major cause. Thus, the use of additional data forces the changes in results and indicates the need of further research on estimated DGSE models with inventories. Moreover, the analysis of welfare-optimal policy in such a theoretical framework would be an interesting prospective task.

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6 Tables and Figures

6.1 Tables

Table 1. Estimation Results for the Model with Inventories

		Prior					Posterior			
		Dis.	Mean	SD	Mode	SD (Hes.)	5%	Med.	Mean	95%
$100\left(\frac{1}{\beta}-1\right)$	Discount factor	G	0.25	0.1	0.24	0.07	0.13	0.25	0.25	0.40
$100(v-1)$	StSt technology growth	N	0.4	0.1	0.32	0.06	0.21	0.32	0.32	0.43
$100(\pi-1)$	StSt inflation	G	0.62	0.1	0.67	0.10	0.53	0.69	0.69	0.86
l_{stst}	StSt hours worked	N	0	2	1.81	1.23	-0.48	1.68	1.69	3.90
b	Consumption habit	B	0.6	0.1	0.79	0.03	0.74	0.79	0.79	0.84
σ_l	Inverse Frisch elasticity	G	2	0.75	1.88	0.52	1.22	1.99	2.02	2.95
θ	Elasticity avail. goods	B	0.5	0.2	0.27	0.09	0.18	0.30	0.31	0.46
μ^p	StSt price markup	G	0.2	0.1	0.64	0.12	0.46	0.62	0.63	0.82
S''	Investment adj. cost	N	4	1.5	4.16	1.00	3.03	4.65	4.68	6.45
σ_a	Elas. capital adj. cost	G	4	1.5	5.42	1.57	3.19	5.40	5.58	8.60
κ_p	Price adjustment cost	G	50	20	51.26	12.63	37.26	56.30	58.72	88.13
κ_w	Wage adjustment cost	G	50	20	64.43	16.89	44.91	71.32	73.04	107.32
γ_p	Price indexation	B	0.5	0.15	0.14	0.07	0.08	0.16	0.17	0.30
γ_w	Wage indexation	B	0.5	0.15	0.13	0.04	0.08	0.13	0.14	0.20
ρ_m	Interest rate smoothing	B	0.75	0.1	0.75	0.02	0.71	0.75	0.75	0.79
φ_π	Response to inflation	N	1.5	0.2	1.83	0.12	1.66	1.85	1.85	2.05
φ_y	Response to output	N	0.13	0.05	0.05	0.01	0.04	0.06	0.06	0.08
$\varphi_{\Delta\pi}$	Resp. to inflation diff.	N	0.3	0.1	0.31	0.07	0.20	0.30	0.30	0.40
$\varphi_{\Delta y}$	Response to output diff.	N	0.06	0.05	0.11	0.02	0.08	0.11	0.11	0.15
ρ_v	technology	B	0.5	0.2	0.18	0.05	0.09	0.18	0.18	0.28
ρ_p	price markup	B	0.5	0.2	0.91	0.05	0.78	0.89	0.88	0.95
ρ_w	wage markup	B	0.5	0.2	0.91	0.03	0.83	0.91	0.91	0.97
ρ_k	capital investment	B	0.5	0.2	0.68	0.08	0.50	0.64	0.64	0.75
ρ_h	storage area investment	B	0.5	0.2	0.35	0.06	0.26	0.36	0.37	0.47
ρ_c	consumption	B	0.5	0.2	0.85	0.04	0.72	0.85	0.84	0.92
ρ_g	government spending	B	0.5	0.2	0.992	0.005	0.980	0.991	0.990	0.997
σ_v	technology	I	0.1	1	1.20	0.11	1.03	1.18	1.18	1.36
σ_p	price markup	I	0.1	1	0.09	0.01	0.07	0.09	0.09	0.12
σ_w	wage markup	I	0.1	1	0.19	0.02	0.16	0.19	0.19	0.24
σ_k	capital investment	I	0.1	1	0.20	0.06	0.16	0.24	0.25	0.36
σ_h	storage area investment	I	0.1	1	0.54	0.04	0.49	0.55	0.55	0.61
σ_c	consumption	I	0.1	1	0.55	0.05	0.48	0.56	0.57	0.66
σ_g	government spending	I	0.1	1	0.49	0.03	0.45	0.49	0.49	0.54
σ_m	interest rate	I	0.1	1	0.28	0.02	0.26	0.28	0.28	0.31

The first three columns show the prior distributions of the estimated parameters. Column 6 reports the estimated posterior mode and column 7 the associated standard errors (taken from the Hessian). The last group contains the posterior distributions obtained by the Random-Walk Metropolis-Hastings algorithm.

Table 2. Estimation Results for the Model without Inventories

		Prior					Posterior			
		Dis.	Mean	SD	Mode	SD (Hes.)	5%	Med.	Mean	95%
$100\left(\frac{1}{\beta}-1\right)$	Discount factor	G	0.25	0.1	0.24	0.08	0.13	0.25	0.26	0.40
$100(v-1)$	StSt technology growth	N	0.4	0.1	0.32	0.07	0.20	0.32	0.32	0.43
$100(\pi-1)$	StSt inflation	G	0.62	0.1	0.68	0.10	0.54	0.69	0.70	0.87
l_{stst}	StSt hours worked	N	0	2	2.31	1.24	-0.21	2.01	1.97	4.09
b	Consumption habit	B	0.6	0.1	0.79	0.03	0.73	0.79	0.79	0.85
σ_l	Inverse Frisch elasticity	G	2	0.75	1.68	0.41	1.18	1.76	1.80	2.55
μ^p	StSt price markup	G	0.2	0.1	0.30	0.06	0.20	0.30	0.30	0.40
S''	Investment adj. cost	N	4	1.5	0.94	0.57	0.68	1.16	1.25	2.09
σ_a	Elas. capital adj. cost	G	4	1.5	7.63	1.70	5.35	7.85	8.00	11.18
κ_p	Price adjustment cost	G	50	20	40.88	13.98	28.27	45.30	47.51	74.20
κ_w	Wage adjustment cost	G	50	20	32.07	10.45	24.33	40.09	42.91	72.92
γ_p	Price indexation	B	0.5	0.15	0.18	0.08	0.10	0.20	0.21	0.34
γ_w	Wage indexation	B	0.5	0.15	0.18	0.05	0.10	0.17	0.17	0.25
ρ_m	Interest rate smoothing	B	0.75	0.1	0.70	0.03	0.66	0.71	0.71	0.76
φ_π	Response to inflation	N	1.5	0.2	1.88	0.11	1.71	1.89	1.90	2.10
φ_y	Response to output	N	0.13	0.05	0.07	0.01	0.05	0.08	0.08	0.10
$\varphi_{\Delta\pi}$	Resp. to inflation diff.	N	0.3	0.1	0.35	0.07	0.23	0.34	0.34	0.45
$\varphi_{\Delta y}$	Response to output diff.	N	0.06	0.05	0.14	0.02	0.11	0.14	0.14	0.18
ρ_v	technology	B	0.5	0.2	0.28	0.06	0.19	0.28	0.28	0.36
ρ_p	price markup	B	0.5	0.2	0.87	0.04	0.77	0.85	0.85	0.91
ρ_w	wage markup	B	0.5	0.2	0.95	0.03	0.88	0.93	0.93	0.97
ρ_k	capital investment	B	0.5	0.2	0.88	0.04	0.79	0.86	0.86	0.91
ρ_c	consumption	B	0.5	0.2	0.82	0.04	0.74	0.84	0.83	0.90
ρ_g	government spending	B	0.5	0.2	0.996	0.005	0.985	0.994	0.993	0.998
σ_v	technology	I	0.1	1	1.08	0.09	0.98	1.10	1.10	1.24
σ_p	price markup	I	0.1	1	0.13	0.02	0.10	0.13	0.13	0.16
σ_w	wage markup	I	0.1	1	0.26	0.03	0.19	0.24	0.25	0.32
σ_k	capital investment	I	0.1	1	0.09	0.02	0.07	0.10	0.10	0.13
σ_c	consumption	I	0.1	1	0.52	0.04	0.47	0.53	0.54	0.61
σ_g	government spending	I	0.1	1	0.48	0.03	0.45	0.49	0.49	0.54
σ_m	interest rate	I	0.1	1	0.29	0.02	0.27	0.30	0.30	0.33

The first three columns show the prior distributions of the estimated parameters. Column 6 reports the estimated posterior mode and column 7 the associated standard errors (taken from the Hessian). The last group contains the posterior distributions obtained by the Random-Walk Metropolis-Hastings algorithm.

Table 3. Variance Decomposition for Model with Inventories I

Variable	**Time**	**Shocks**							
		η_t^c *cons.*	η_t^k *cap.*	η_t^w *wage*	η_t^v *tech.*	η_t^p *price*	η_t^s *gov.*	η_t^r *mon.*	η_t^h *stor.*
Output	t=0	3.8	37.2	3.5	11.2	4.8	12.9	1.4	24.4
		[2.9, 5.0]	[31.1, 43.4]	[1.8, 6.1]	[8.1, 15.4]	[3.1, 7.0]	[10.5, 15.6]	[0.8, 2.5]	[20.2, 29.1]
	t=4	4.1	34.4	13.9	25.8	12.8	3.5	1.1	3.0
		[2.6, 6.5]	[26.1, 44.4]	[7.2, 22.5]	[19.5, 33.1]	[7.8, 19.0]	[2.6, 4.7]	[0.6, 2.0]	[2.2, 4.1]
	t=10	2.3	21.8	20.6	35.7	13.4	1.9	0.6	1.2
		[1.2, 5.0]	[14.1, 32.8]	[10.0, 34.5]	[27.1, 45.2]	[6.2, 24.7]	[1.3, 2.8]	[0.3, 1.1]	[0.8, 1.8]
	t=20	1.3	14.6	18.8	48.1	10.8	1.5	0.3	0.8
		[0.6, 3.2]	[8.5, 24.2]	[7.9, 37.5]	[36.4, 59.5]	[3.9, 26.0]	[0.9, 2.5]	[0.2, 0.6]	[0.5, 1.2]
	t=40	0.8	9.0	12.2	65.0	7.2	1.3	0.2	0.5
		[0.4, 1.9]	[5.0, 15.8]	[4.7, 32.2]	[49.6, 75.6]	[2.3, 22.7]	[0.6, 2.5]	[0.1, 0.4]	[0.3, 0.7]
Sales	t=0	5.3	50.0	3.8	13.7	6.9	16.7	1.7	1.1
		[4.1, 7.0]	[43.3, 56.5]	[1.8, 6.7]	[9.8, 18.7]	[4.3, 10.1]	[13.5, 20.6]	[1.0, 3.0]	[0.7, 1.6]
	t=4	5.2	41.2	10.1	23.0	13.4	4.5	1.3	0.2
		[3.1, 7.5]	[28.4, 47.7]	[5.9, 20.0]	[18.7, 32.6]	[8.6, 22.1]	[2.7, 4.9]	[0.6, 1.9]	[0.1, 0.3]
	t=10	2.8	23.3	17.7	35.1	15.7	2.0	0.5	0.2
		[1.4, 5.9]	[15.0, 35.0]	[8.3, 31.2]	[26.2, 45.0]	[7.0, 28.5]	[1.4, 2.9]	[0.3, 1.0]	[0.1, 0.4]
	t=20	1.7	15.2	16.5	48.0	12.6	1.6	0.3	0.1
		[0.8, 3.9]	[8.8, 25.3]	[6.7, 34.8]	[35.8, 59.8]	[4.4, 29.9]	[1.0, 2.6]	[0.2, 0.6]	[0.0, 0.3]
	t=40	1.0	9.2	11.0	65.0	8.1	1.3	0.2	0.1
		[0.5, 2.4]	[5.1, 16.2]	[4.1, 30.6]	[49.5, 75.8]	[2.5, 24.6]	[0.7, 2.6]	[0.1, 0.4]	[0.0, 0.2]
Inventories	t=0	0.1	0.2	0.1	0.0	0.1	0.0	0.0	99.5
		[0.0, 0.1]	[0.0, 0.5]	[0.1, 0.2]	[0.0, 0.1]	[0.0, 0.4]	[0.0, 0.0]	[0.0, 0.0]	[98.9, 99.7]
	t=4	0.8	1.6	2.1	0.2	1.4	0.0	0.0	93.2
		[0.4, 1.3]	[0.3, 5.1]	[1.3, 3.4]	[0.1, 0.4]	[0.2, 5.5]	[0.0, 0.1]	[0.0, 0.1]	[87.3, 96.5]
	t=10	3.0	3.1	8.4	0.4	6.7	0.1	0.0	75.7
		[1.5, 5.5]	[0.4, 11.3]	[4.9, 13.2]	[0.1, 0.8]	[0.8, 23.3]	[0.0, 0.3]	[0.0, 0.1]	[59.2, 87.0]
	t=20	6.3	1.8	18.2	0.3	15.1	0.3	0.0	52.4
		[2.6, 13.8]	[0.5, 8.9]	[10.0, 29.0]	[0.1, 1.2]	[1.8, 47.3]	[0.1, 0.8]	[0.0, 0.1]	[30.5, 71.5]
	t=40	8.6	9.0	28.5	1.8	12.7	0.5	0.0	30.2
		[2.8, 22.6]	[4.5, 16.6]	[13.0, 46.9]	[0.5, 4.5]	[1.3, 51.5]	[0.1, 1.5]	[0.0, 0.1]	[15.0, 48.2]
Ratio	t=0	5.5	50.3	3.4	13.1	7.1	16.5	1.6	1.7
Inventories		[4.2, 7.1]	[43.6, 56.9]	[1.5, 6.1]	[9.4, 17.8]	[4.4, 10.6]	[13.3, 20.4]	[0.9, 2.8]	[1.1, 2.6]
to Output	t=4	4.5	29.4	4.2	14.0	12.8	2.5	0.5	29.9
		[2.9, 7.0]	[20.9, 39.4]	[1.8, 8.3]	[10.0, 19.0]	[6.3, 22.1]	[1.8, 3.5]	[0.3, 1.0]	[21.7, 41.2]
	t=10	4.2	19.3	2.1	14.5	18.3	1.4	0.2	35.5
		[2.1, 8.4]	[10.4, 32.7]	[0.8, 6.1]	[9.4, 21.0]	[6.1, 38.9]	[0.9, 2.1]	[0.1, 0.4]	[22.7, 52.4]
	t=20	5.1	11.6	3.4	16.2	24.2	1.3	0.1	32.4
		[2.0, 11.8]	[4.6, 24.5]	[1.9, 5.6]	[9.1, 24.7]	[5.6, 57.3]	[0.7, 2.1]	[0.0, 0.2]	[16.6, 52.7]
	t=40	6.5	11.2	10.4	18.8	21.2	1.7	0.1	22.7
		[2.3, 17.4]	[4.6, 21.4]	[4.6, 17.4]	[9.2, 28.6]	[3.9, 61.9]	[0.8, 2.7]	[0.0, 0.2]	[9.9, 39.7]

Medians and 5th/95th percentiles. Percentage values.

Table 4. Variance Decomposition for Model with Inventories II

Variable	**Time**	**Shocks**							
		η_t^c *cons.*	η_t^k *cap.*	η_t^w *wage*	η_t^v *tech.*	η_t^p *price*	η_t^s *gov.*	η_t^r *mon.*	η_t^h *stor.*
Gross Investment	t=0	0.9	54.1	1.6	5.9	2.5	0.1	0.7	33.8
		[0.5, 1.4]	[47.5, 60.3]	[0.9, 2.8]	[4.0, 8.8]	[1.4, 4.0]	[0.0, 0.1]	[0.4, 1.4]	[28.4, 39.6]
	t=4	3.0	61.1	8.1	12.6	8.2	0.1	0.7	5.1
		[1.6, 5.3]	[50.0, 71.7]	[4.5, 12.7]	[8.5, 18.4]	[4.3, 13.4]	[0.0, 0.3]	[0.4, 1.4]	[3.6, 7.3]
	t=10	4.8	43.8	15.2	19.8	11.2	0.1	0.5	2.6
		[2.2, 9.2]	[30.6, 58.9]	[8.0, 23.7]	[13.7, 27.6]	[4.7, 21.4]	[0.0, 0.4]	[0.2, 0.9]	[1.7, 3.9]
	t=20	4.7	32.5	16.4	29.6	10.8	0.1	0.3	2.1
		[1.9, 10.2]	[20.4, 47.6]	[7.6, 28.6]	[21.4, 39.1]	[3.8, 25.9]	[0.0, 0.4]	[0.2, 0.6]	[1.4, 3.2]
	t=40	3.7	25.3	13.0	43.2	8.7	0.1	0.3	1.7
		[1.4, 8.2]	[15.1, 38.9]	[5.9, 26.1]	[32.5, 54.0]	[2.9, 24.9]	[0.0, 0.4]	[0.1, 0.5]	[1.1, 2.6]
Fixed Investment	t=0	0.9	84.6	1.6	7.1	4.5	0.1	0.9	0.1
		[0.5, 1.5]	[78.0, 89.4]	[0.8, 2.9]	[4.6, 10.5]	[2.4, 7.6]	[0.0, 0.1]	[0.5, 1.7]	[0.0, 0.3]
	t=4	2.2	68.2	5.8	11.1	10.8	0.1	0.7	0.2
		[1.1, 3.9]	[56.3, 78.7]	[3.0, 9.6]	[7.3, 16.6]	[5.3, 18.6]	[0.0, 0.2]	[0.4, 1.2]	[0.1, 0.5]
	t=10	3.5	48.9	11.2	18.3	15.3	0.1	0.4	0.2
		[1.6, 6.9]	[33.3, 64.6]	[5.5, 18.6]	[12.2, 26.3]	[6.1, 29.8]	[0.0, 0.3]	[0.2, 0.8]	[0.1, 0.7]
	t=20	3.5	36.6	12.4	28.3	15.0	0.1	0.3	0.2
		[1.4, 7.7]	[22.0, 52.7]	[5.4, 23.5]	[19.6, 38.7]	[5.1, 35.1]	[0.0, 0.3]	[0.2, 0.6]	[0.1, 0.6]
	t=40	2.8	29.5	10.0	41.1	12.0	0.1	0.2	0.2
		[1.1, 6.2]	[17.0, 44.5]	[4.3, 21.9]	[29.6, 53.0]	[3.9, 31.7]	[0.0, 0.3]	[0.1, 0.5]	[0.1, 0.5]
Capital Investment	t=0	0.9	87.7	1.7	3.6	4.7	0.1	0.9	0.1
		[0.5, 1.5]	[81.4, 92.1]	[0.8, 3.0]	[2.2, 6.0]	[2.5, 7.9]	[0.0, 0.1]	[0.5, 1.8]	[0.0, 0.3]
	t=4	2.3	70.7	6.0	7.9	11.2	0.1	0.7	0.2
		[1.2, 4.1]	[58.8, 80.9]	[3.1, 10.1]	[5.0, 12.5]	[5.5, 19.3]	[0.0, 0.2]	[0.4, 1.3]	[0.1, 0.6]
	t=10	3.7	51.4	11.8	14.2	16.1	0.1	0.4	0.3
		[1.6, 7.2]	[35.3, 67.3]	[5.8, 19.7]	[9.0, 21.4]	[6.4, 31.4]	[0.0, 0.3]	[0.2, 0.9]	[0.1, 0.7]
	t=20	3.8	39.4	13.3	22.8	16.1	0.1	0.3	0.2
		[1.5, 8.3]	[23.8, 56.4]	[5.9, 25.1]	[14.9, 32.6]	[5.5, 37.7]	[0.0, 0.3]	[0.2, 0.7]	[0.1, 0.7]
	t=40	3.1	33.1	11.3	34.0	13.4	0.1	0.3	0.2
		[1.2, 7.0]	[19.1, 49.3]	[4.9, 24.3]	[22.8, 46.1]	[4.4, 35.3]	[0.0, 0.3]	[0.1, 0.6]	[0.1, 0.6]
Consumption	t=0	62.4	0.8	7.1	19.5	3.7	3.6	1.4	0.1
		[51.7, 73.4]	[0.0, 3.5]	[3.6, 13.7]	[13.2, 26.3]	[2.0, 6.4]	[1.9, 6.2]	[0.6, 2.8]	[0.0, 0.2]
	t=4	50.3	0.3	11.6	25.3	4.9	4.8	0.6	0.1
		[37.5, 63.8]	[0.1, 1.9]	[5.3, 24.3]	[19.0, 32.5]	[2.6, 8.9]	[2.4, 8.1]	[0.3, 1.1]	[0.0, 0.2]
	t=10	34.7	1.8	14.4	34.3	4.9	6.2	0.3	0.0
		[19.6, 52.6]	[1.1, 2.9]	[5.7, 33.5]	[26.0, 42.8]	[2.1, 10.9]	[2.9, 10.8]	[0.1, 0.5]	[0.0, 0.1]
	t=20	18.5	6.5	13.1	45.8	4.4	6.8	0.1	0.0
		[8.3, 34.9]	[3.9, 10.6]	[4.6, 35.2]	[35.5, 55.3]	[1.4, 13.0]	[3.2, 11.8]	[0.1, 0.3]	[0.0, 0.1]
	t=40	8.8	6.6	9.0	61.2	3.4	6.0	0.1	0.0
		[3.7, 18.3]	[3.6, 11.8]	[2.9, 30.8]	[48.2, 70.6]	[0.9, 14.0]	[2.8, 10.8]	[0.0, 0.2]	[0.0, 0.0]

Medians and 5th/95th percentiles. Percentage values.

Table 5. Variance Decomposition for Model with Inventories III

Variable	**Time**	**Shocks**							
		η_t^c *cons.*	η_t^k *cap.*	η_t^w *wage*	η_t^v *tech.*	η_t^p *price*	η_t^s *gov.*	η_t^r *mon.*	η_t^h *stor.*
Real Wage	t=0	0.1	5.2	43.1	11.5	35.8	0.0	2.4	0.5
		[0.0, 0.9]	[2.1, 9.8]	[32.8, 55.5]	[7.1, 17.5]	[26.8, 44.7]	[0.0, 0.2]	[1.3, 4.1]	[0.1, 1.5]
	t=4	0.1	6.8	21.4	26.6	42.5	0.0	1.2	0.1
		[0.0, 0.6]	[3.7, 11.4]	[13.9, 32.3]	[19.5, 35.4]	[31.0, 53.2]	[0.0, 0.1]	[0.7, 2.2]	[0.0, 0.2]
	t=10	0.0	7.3	10.9	37.8	42.0	0.0	0.6	0.1
		[0.0, 0.4]	[4.1, 12.4]	[6.3, 18.5]	[27.2, 49.7]	[26.3, 56.8]	[0.0, 0.1]	[0.3, 1.2]	[0.0, 0.3]
	t=20	0.1	6.7	6.1	52.7	32.5	0.1	0.4	0.1
		[0.0, 0.5]	[3.4, 12.1]	[3.3, 10.8]	[36.4, 66.6]	[16.4, 53.3]	[0.0, 0.1]	[0.2, 0.7]	[0.0, 0.5]
	t=40	0.1	4.4	3.5	70.6	19.9	0.1	0.2	0.1
		[0.0, 0.4]	[2.2, 8.4]	[1.9, 6.1]	[50.8, 81.7]	[8.7, 42.7]	[0.0, 0.1]	[0.1, 0.4]	[0.0, 0.3]
Hours	t=0	4.0	37.8	4.9	8.2	4.0	13.5	1.3	25.4
Worked		[3.1, 5.3]	[32.1, 43.8]	[2.8, 7.9]	[5.6, 11.4]	[2.4, 6.0]	[11.1, 16.6]	[0.7, 2.5]	[21.1, 30.2]
	t=4	7.4	35.3	25.7	2.1	15.3	5.9	1.6	5.0
		[4.6, 12.0]	[26.4, 45.6]	[14.4, 38.7]	[1.5, 3.2]	[9.4, 23.0]	[4.4, 8.0]	[0.9, 2.8]	[3.7, 6.9]
	t=10	6.2	20.6	42.4	2.5	17.8	4.4	0.9	2.6
		[2.8, 13.8]	[12.9, 31.5]	[21.8, 62.8]	[1.6, 3.6]	[8.2, 32.5]	[2.9, 6.5]	[0.5, 1.8]	[1.8, 3.8]
	t=20	5.6	16.8	46.4	3.1	16.4	5.0	0.7	2.1
		[1.9, 14.9]	[9.0, 27.3]	[21.0, 72.6]	[1.6, 5.1]	[6.0, 36.1]	[2.8, 8.1]	[0.3, 1.5]	[1.3, 3.3]
	t=40	5.5	16.8	44.3	3.6	15.4	6.8	0.7	2.0
		[1.6, 15.6]	[8.0, 27.7]	[19.2, 75.2]	[1.7, 6.0]	[5.2, 35.5]	[3.4, 11.6]	[0.3, 1.4]	[1.1, 3.2]
Inflation	t=0	1.2	5.7	27.9	1.8	58.8	0.01	2.5	1.0
		[0.2, 2.3]	[1.4, 13.1]	[21.2, 34.6]	[0.7, 3.8]	[47.4, 70.7]	[0.0, 0.2]	[1.3, 4.6]	[0.5, 1.9]
	t=4	2.3	6.5	40.4	1.1	43.5	0.1	3.4	0.9
		[0.7, 4.1]	[1.2, 16.4]	[31.3, 48.8]	[0.5, 2.2]	[31.6, 58.7]	[0.0, 0.3]	[1.8, 6.3]	[0.5, 1.9]
	t=10	2.8	6.4	42.2	2.7	39.4	0.1	3.3	0.9
		[1.2, 4.9]	[1.7, 15.6]	[32.0, 52.2]	[1.5, 4.4]	[27.9, 55.4]	[0.0, 0.6]	[1.7, 6.1]	[0.4, 1.8]
	t=20	2.9	8.5	41.0	3.6	37.6	0.2	3.0	0.8
		[1.4, 5.1]	[3.3, 17.2]	[30.0, 53.2]	[2.0, 5.8]	[25.5, 54.3]	[0.1, 1.1]	[1.6, 5.6]	[0.4, 1.7]
	t=40	3.0	9.5	40.1	3.8	36.8	0.3	2.8	0.8
		[1.4, 5.3]	[4.0, 18.5]	[28.0, 56.0]	[2.1, 6.2]	[23.3, 54.6]	[0.1, 2.1]	[1.4, 5.3]	[0.4, 1.6]
Interest	t=0	1.3	10.9	0.7	11.0	2.2	2.4	64.9	5.6
Rate		[0.8, 2.0]	[7.4, 15.2]	[0.1, 2.3]	[7.0, 15.8]	[0.4, 5.4]	[1.4, 3.6]	[54.6, 74.9]	[3.4, 8.7]
	t=4	5.5	30.0	13.0	7.0	14.8	1.2	24.9	2.4
		[3.5, 8.0]	[18.0, 42.1]	[8.4, 18.5]	[4.4, 10.6]	[9.3, 22.0]	[0.7, 1.9]	[19.0, 31.9]	[1.4, 4.1]
	t=10	7.7	29.4	19.6	6.2	14.0	0.9	18.6	1.9
		[4.9, 11.4]	[15.8, 44.4]	[12.8, 27.6]	[4.2, 9.0]	[8.4, 22.6]	[0.5, 1.5]	[14.0, 24.0]	[1.1, 3.4]
	t=20	8.2	28.5	20.4	8.0	13.3	0.9	17.0	1.8
		[4.9, 12.3]	[15.7, 42.7]	[12.9, 30.0]	[5.6, 11.2]	[7.9, 22.3]	[0.5, 1.4]	[12.7, 22.0]	[1.0, 3.2]
	t=40	7.9	28.9	20.6	8.5	13.4	0.9	15.5	1.6
		[4.5, 12.5]	[16.3, 42.9]	[12.6, 33.9]	[5.8, 12.0]	[7.8, 24.4]	[0.5, 1.6]	[11.3, 20.3]	[0.9, 3.0]

Medians and 5th/95th percentiles. Percentage values.

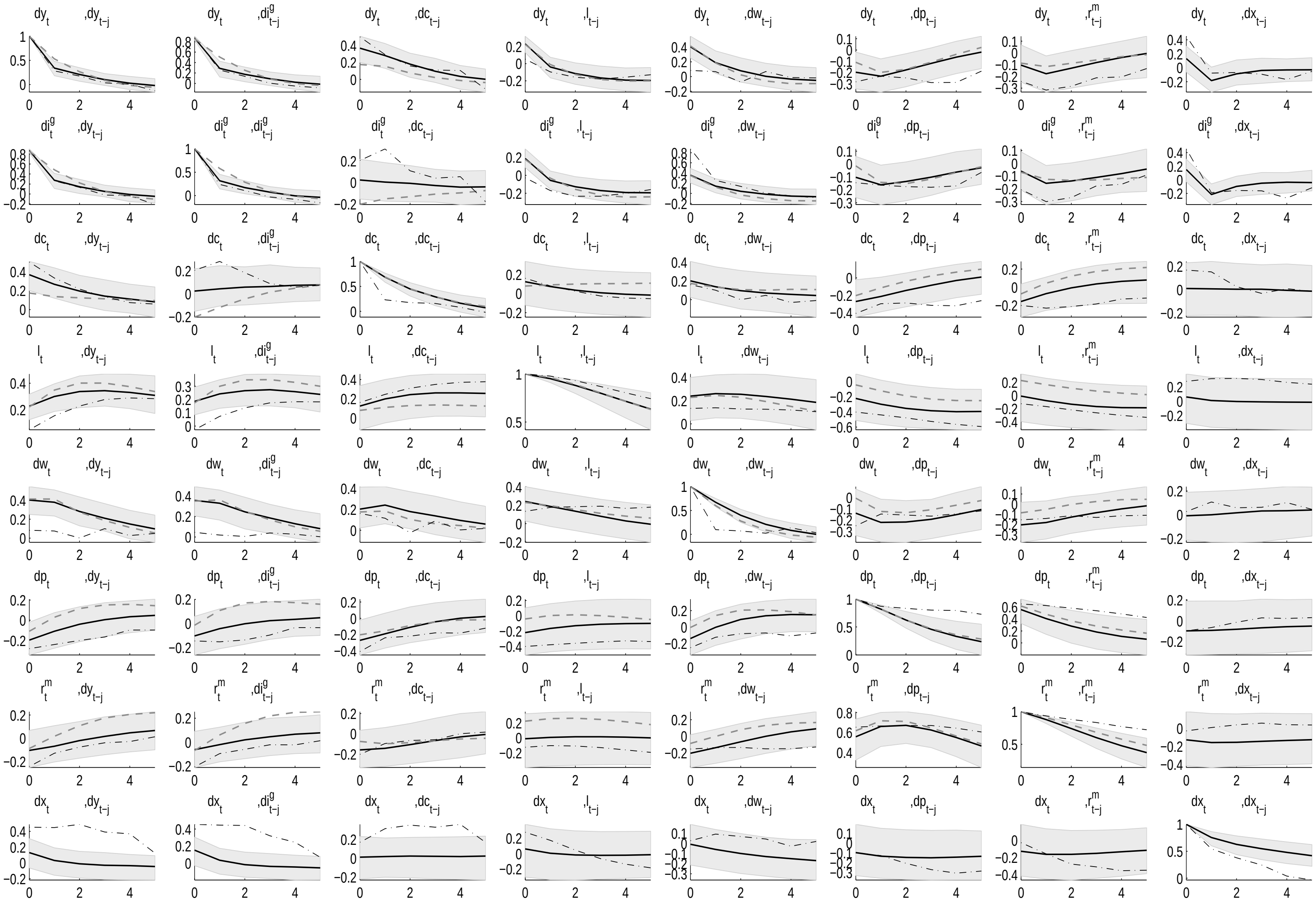
Table 6. Variance Decomposition for Model without Inventories

Variable	**Time**				**Shock**			
		η_t^c *cons.*	η_t^k *cap.*	η_t^w *wage*	η_t^v *tech.*	η_t^p *price*	η_t^g *gov.*	η_t^m *mon.*
Output	t=0	2.1	41.4	5.5	23.9	9.0	12.0	5.2
	t=4	2.1	30.2	18.1	33.8	11.7	2.1	1.6
	t=10	0.6	22.0	24.9	40.7	8.2	1.4	0.7
	t=20	0.4	16.4	23.0	51.5	5.3	1.3	0.4
	t=40	0.3	10.7	16.1	66.5	3.2	1.3	0.2
Investment	t=0	2.5	68.0	3.1	14.1	7.2	0.4	4.1
	t=4	4.4	56.2	10.9	16.6	9.4	0.2	1.2
	t=10	5.6	48.1	16.7	19.6	7.6	0.1	0.6
	t=20	5.3	41.5	18.2	26.5	6.2	0.1	0.5
	t=40	4.5	34.9	16.1	36.9	5.2	0.2	0.4
Consumption	t=0	59.5	13.2	4.5	16.7	0.5	3.9	0.6
	t=4	49.3	11.7	8.1	23.1	0.7	5.3	0.2
	t=10	34.4	6.1	12.0	36.5	0.8	7.6	0.1
	t=20	16.8	7.0	13.1	50.9	1.1	8.3	0.1
	t=40	7.4	8.8	9.8	63.9	0.8	6.8	0.0
Real Wage	t=0	0.3	0.3	41.6	19.7	33.2	0.1	3.8
	t=4	0.2	1.3	17.6	42.9	35.3	0.2	1.4
	t=10	0.3	3.5	8.9	57.6	27.8	0.2	0.7
	t=20	0.5	5.8	4.8	70.5	16.9	0.2	0.4
	t=40	0.4	5.1	2.7	81.9	8.6	0.2	0.2
Hours Worked	t=0	2.8	52.6	8.4	3.3	10.2	15.4	6.3
	t=4	2.6	39.8	31.9	1.5	16.6	3.9	2.4
	t=10	2.2	27.3	49.2	2.0	13.2	3.5	1.3
	t=20	2.1	22.7	54.8	2.3	11.0	4.7	1.1
	t=40	2.1	22.0	53.6	2.4	10.2	6.9	1.0
Inflation	t=0	0.4	18.9	36.8	0.4	31.9	0.0	6.5
	t=4	0.9	26.8	40.7	2.1	21.8	0.2	6.2
	t=10	1.2	25.6	41.9	4.5	19.5	0.4	5.6
	t=20	1.5	24.9	42.9	5.4	17.8	0.6	5.0
	t=40	1.7	26.0	42.8	5.6	16.2	1.0	4.5
Interest Rate	t=0	0.9	23.5	1.0	9.3	0.8	2.9	60.6
	t=4	2.1	67.2	9.5	3.3	2.9	0.8	13.6
	t=10	2.5	70.3	10.4	4.7	2.0	0.6	9.2
	t=20	2.9	66.5	12.4	6.4	2.0	0.6	8.5
	t=40	3.1	63.6	14.7	6.9	2.1	0.7	7.7

Medians as percentage values.

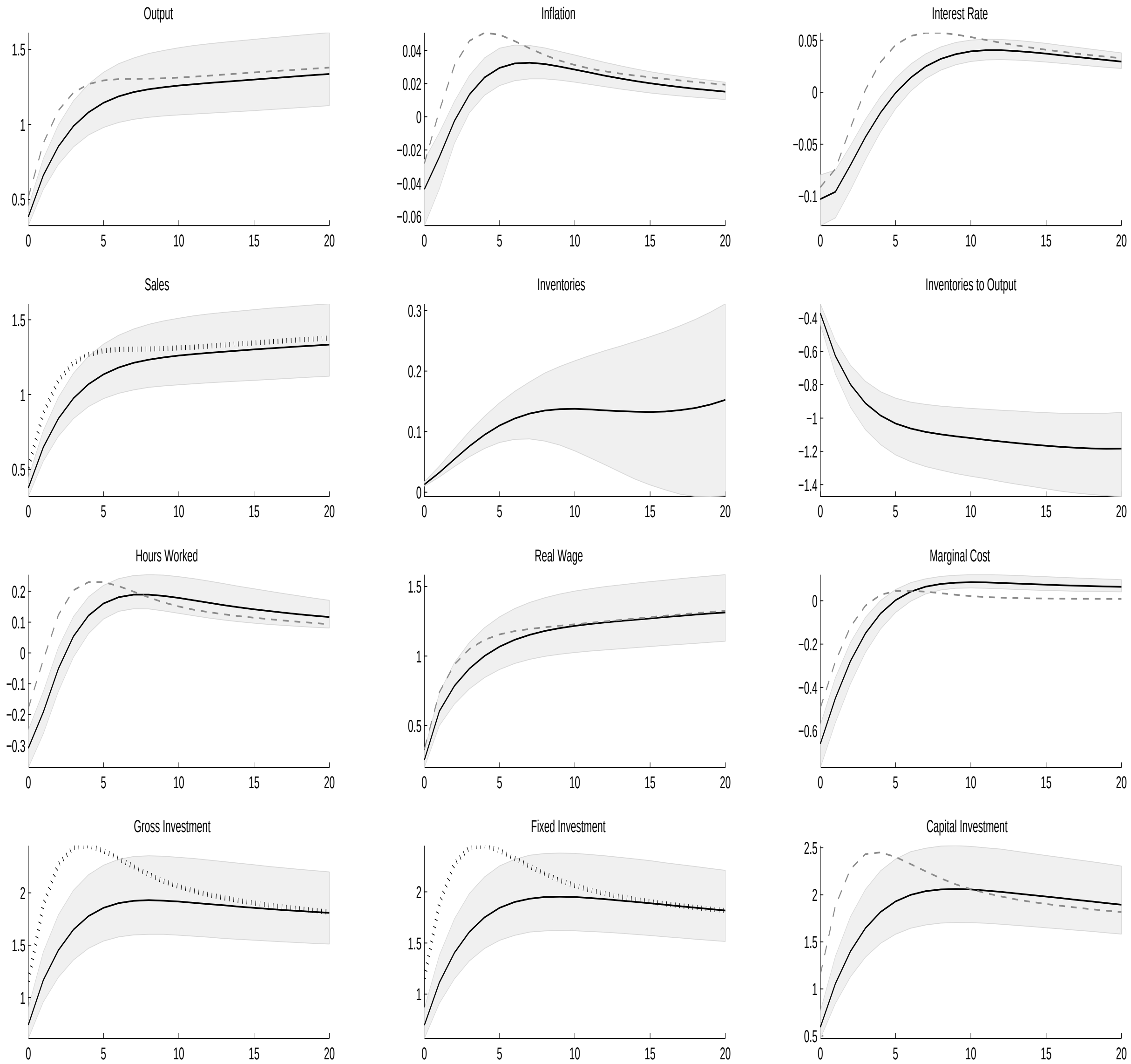
6.2 Figures

Figure 1. Correlations



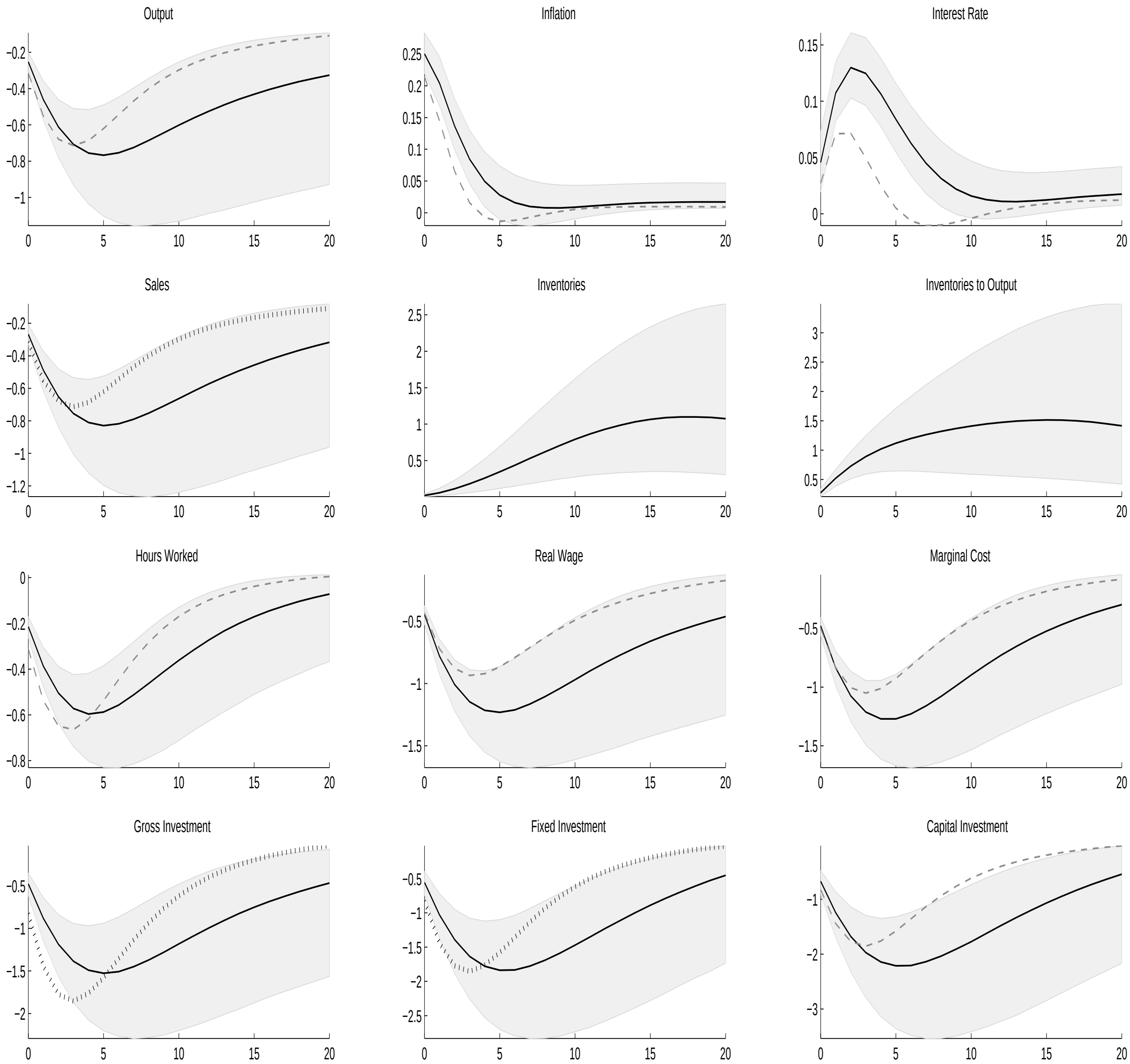
The black and gray lines show the median and the 5% & 95% percentile correlations of the estimated model with inventories, respectively. The dashed gray line reveals the median correlations of the estimated model without inventories. The dash-dotted black line stands for correlations in the data.

Figure 2. Response to a Technology Shock



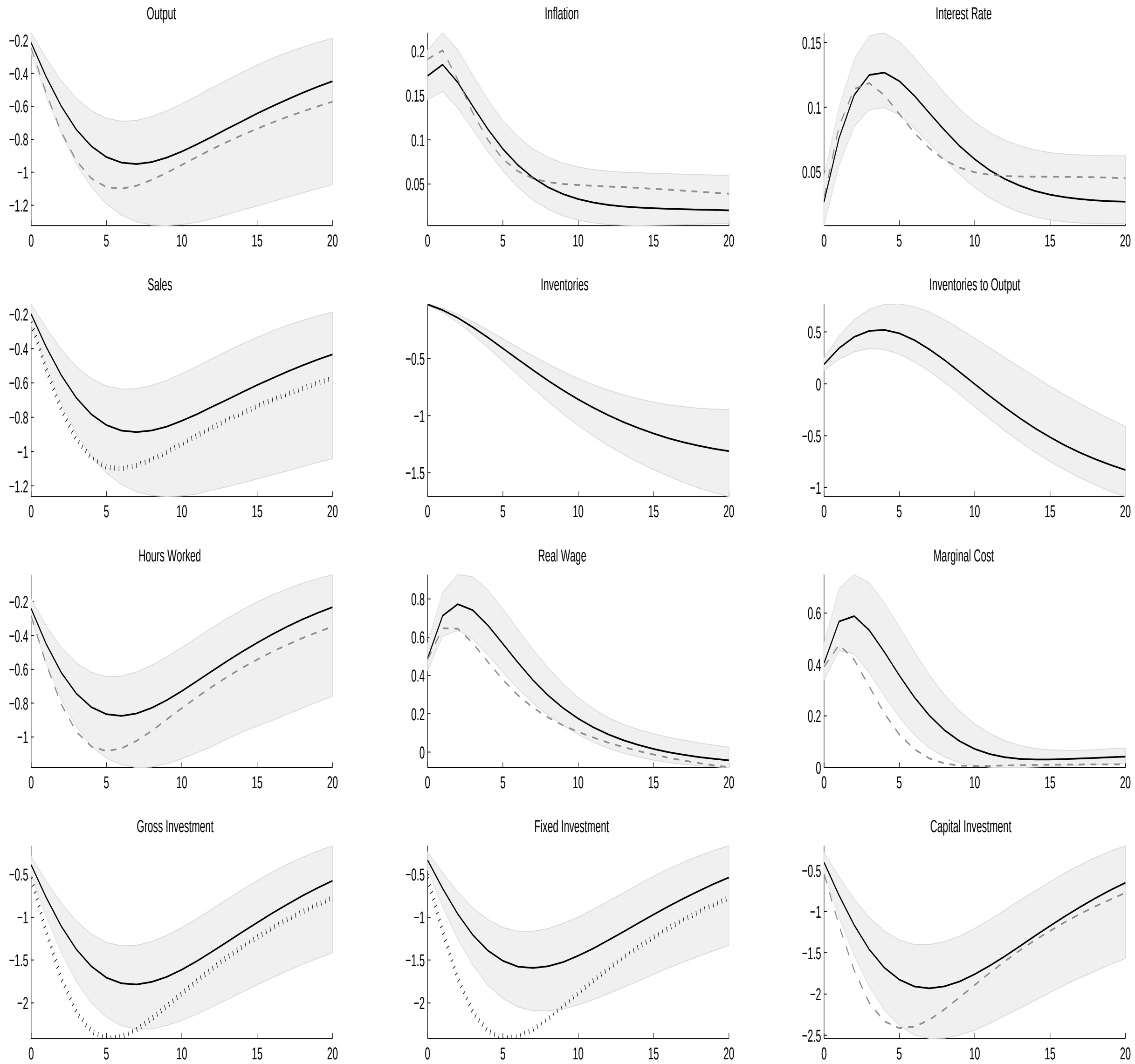
Medians, 5% and 95% percentile responses (solid lines). Dashed lines are median responses for the estimated model without inventories. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 3. Response to a Price Markup Shock



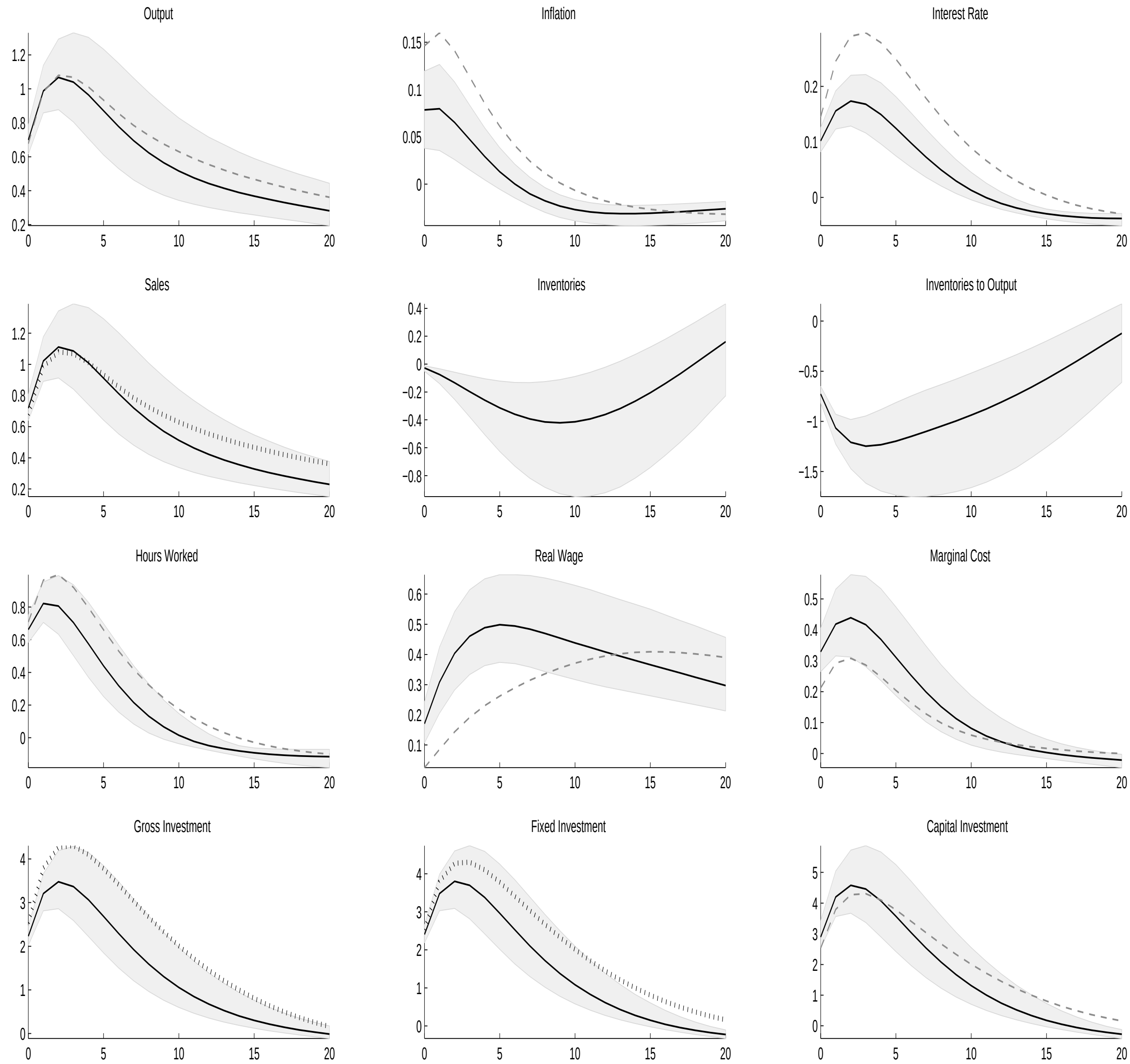
Medians, 5% and 95% percentile responses (solid lines). Dashed lines are median responses for the estimated model without inventories. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 4. Response to a Wage Markup Shock



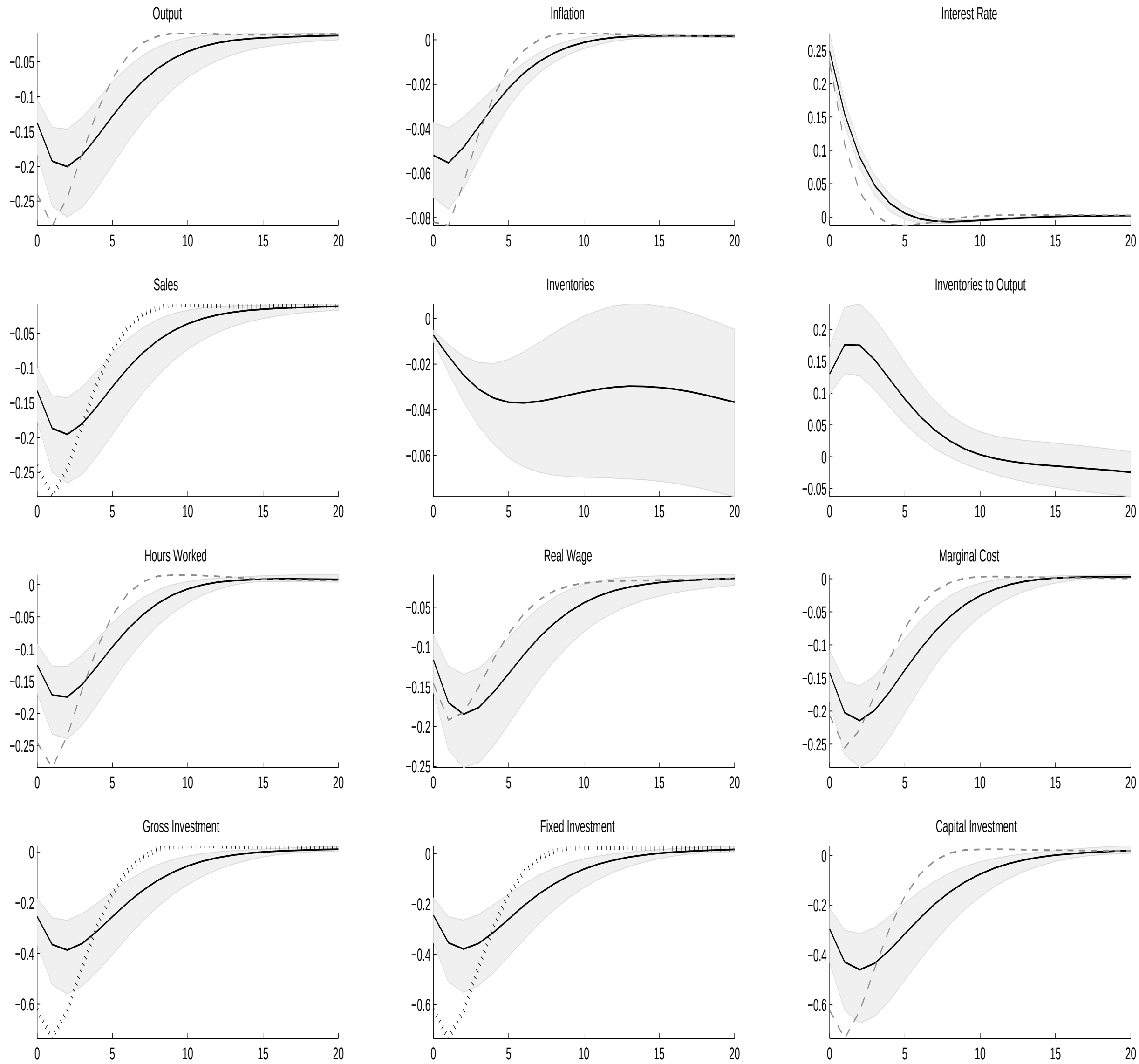
Medians, 5% and 95% percentile responses (solid lines). Dashed lines are median responses for the estimated model without inventories. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 5. Response to a Capital Investment Shock



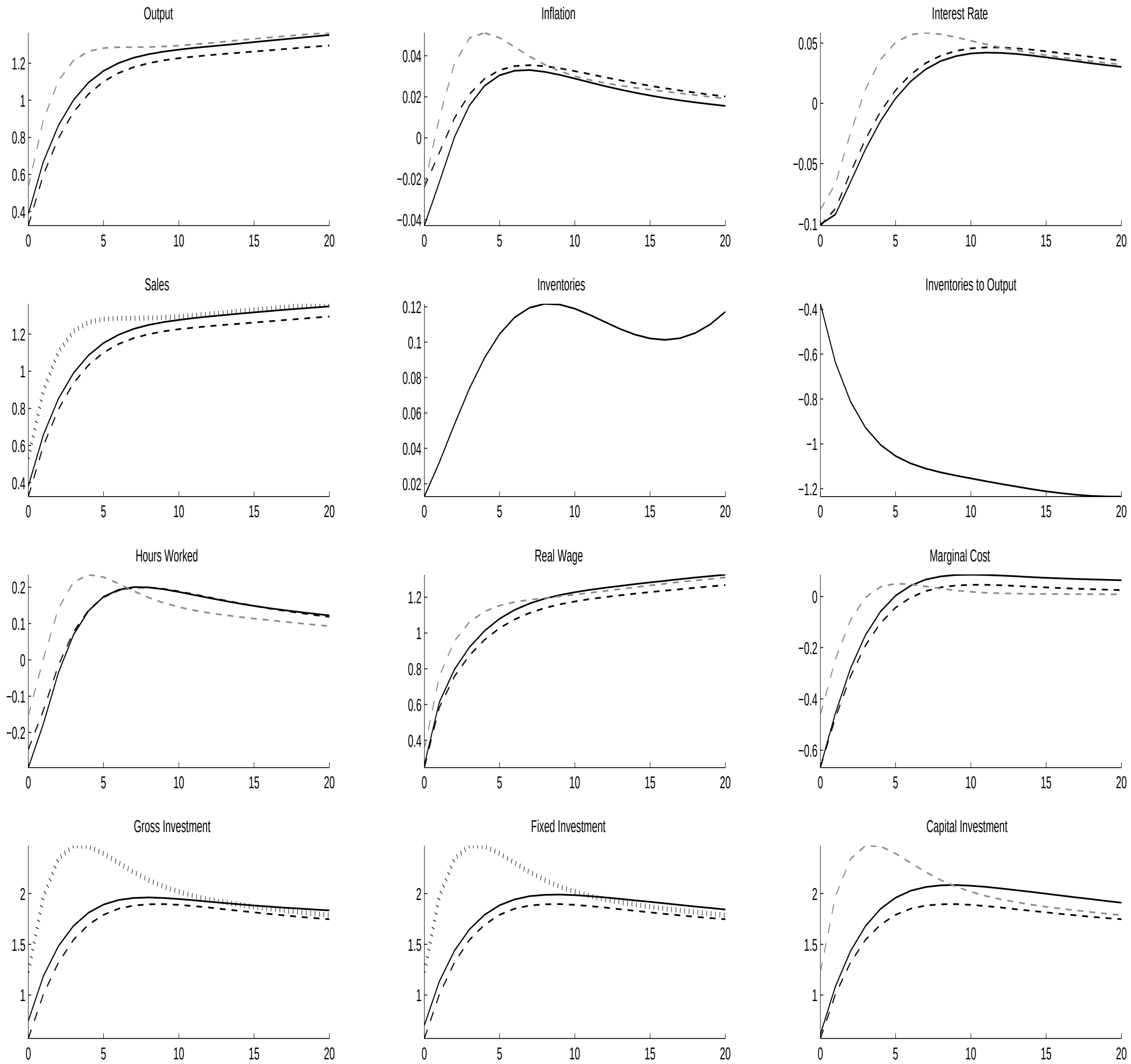
Medians, 5% and 95% percentile responses (solid lines). Dashed lines are median responses for the estimated model without inventories. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 6. Response to a Monetary Policy Shock



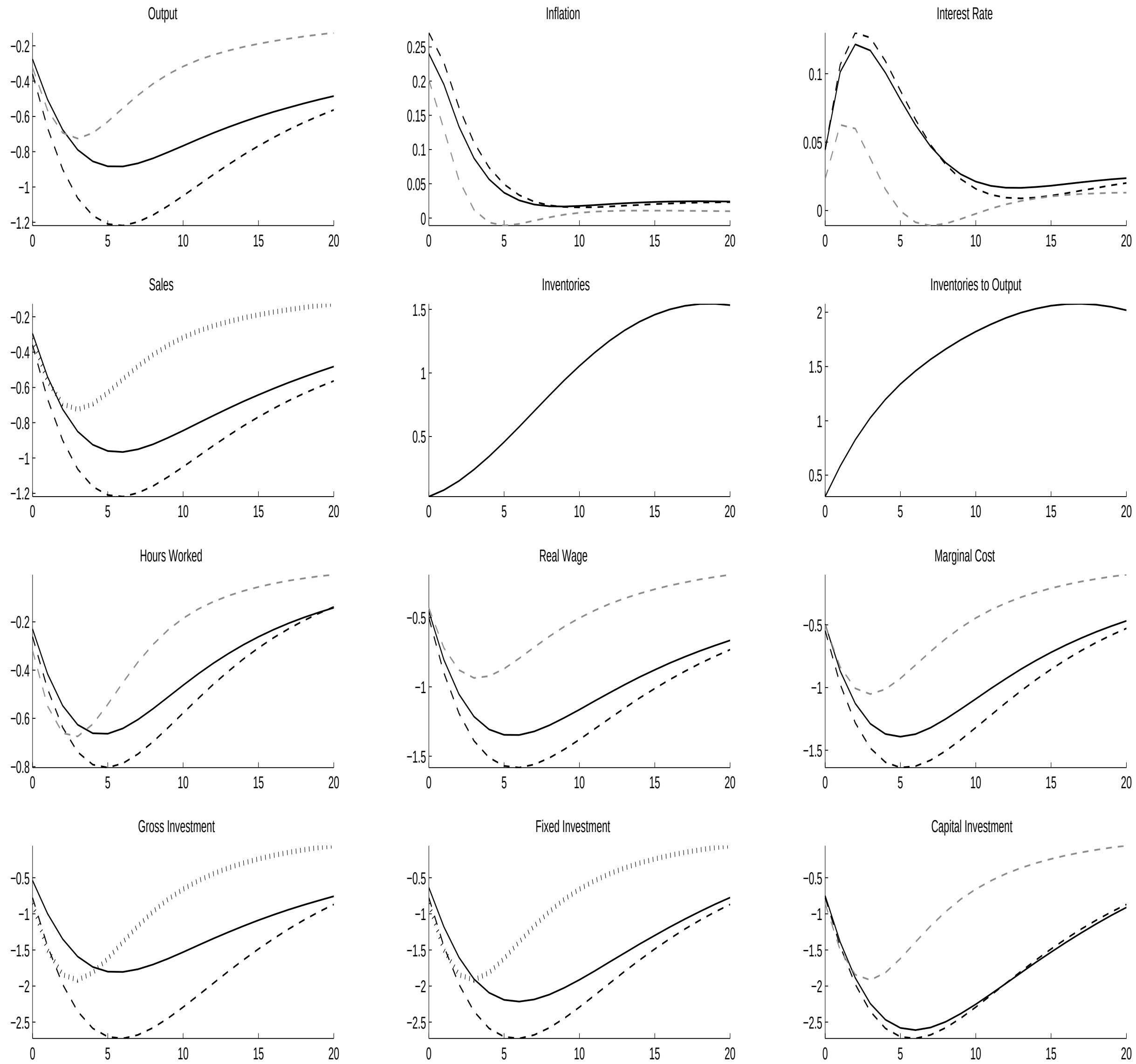
Medians, 5% and 95% percentile responses (solid lines). Dashed lines are median responses for the estimated model without inventories. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 7. Counterfactual Responses to Technology Shocks: Same Parameters



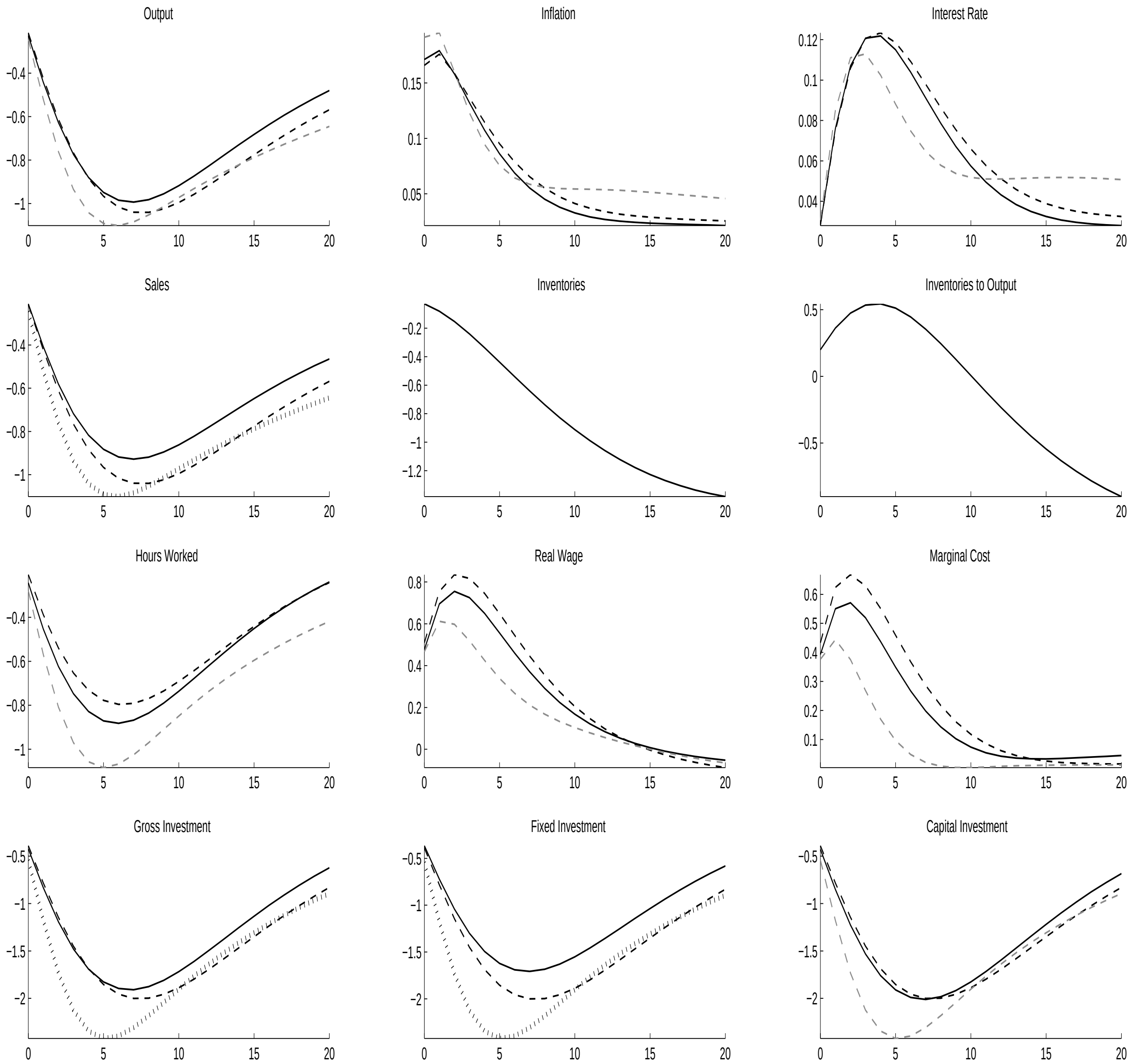
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 8. Counterfactual Responses to Price Markup Shocks: Same Parameters



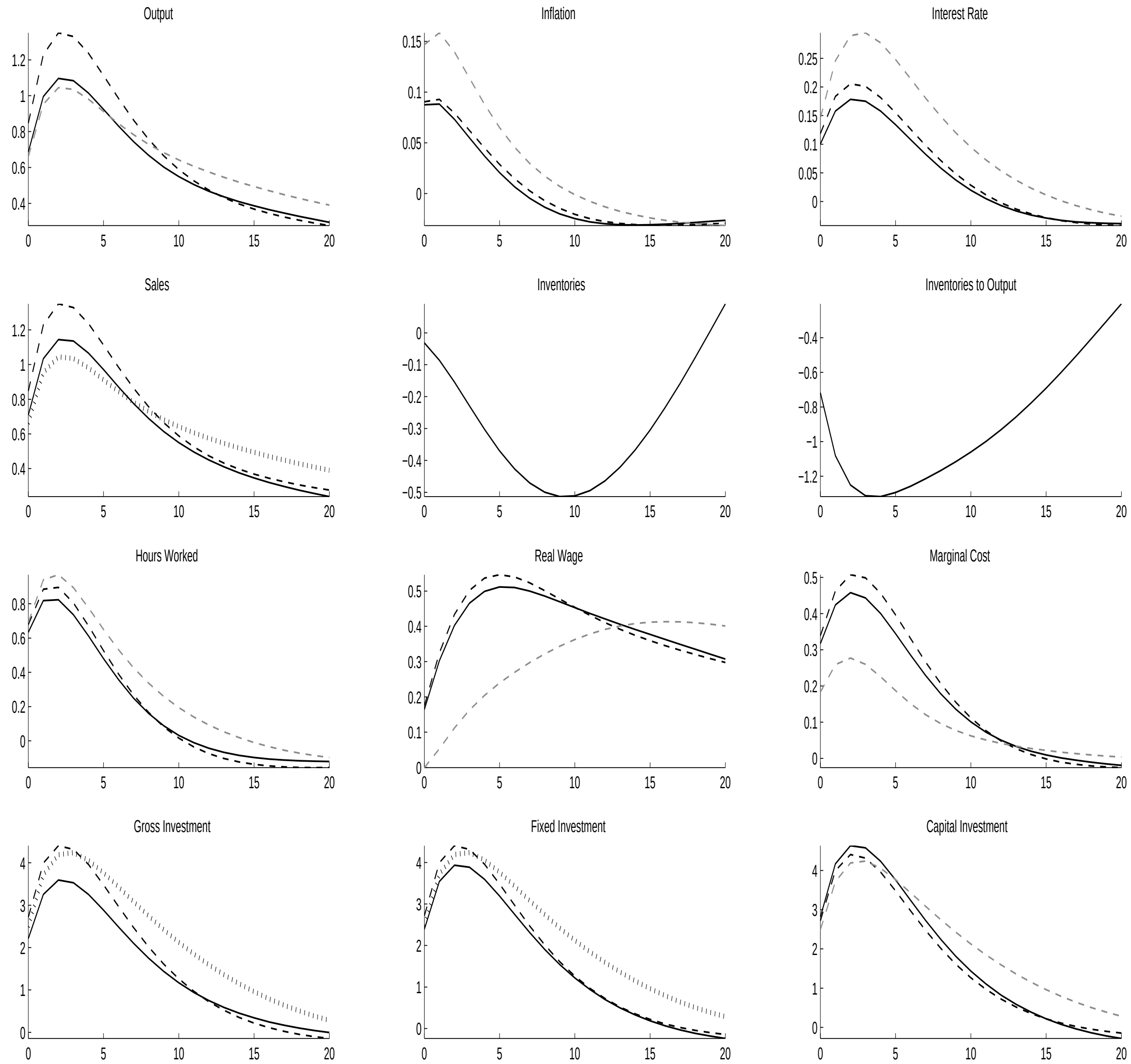
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 9. Counterfactual Responses to Wage Markup Shocks: Same Parameters



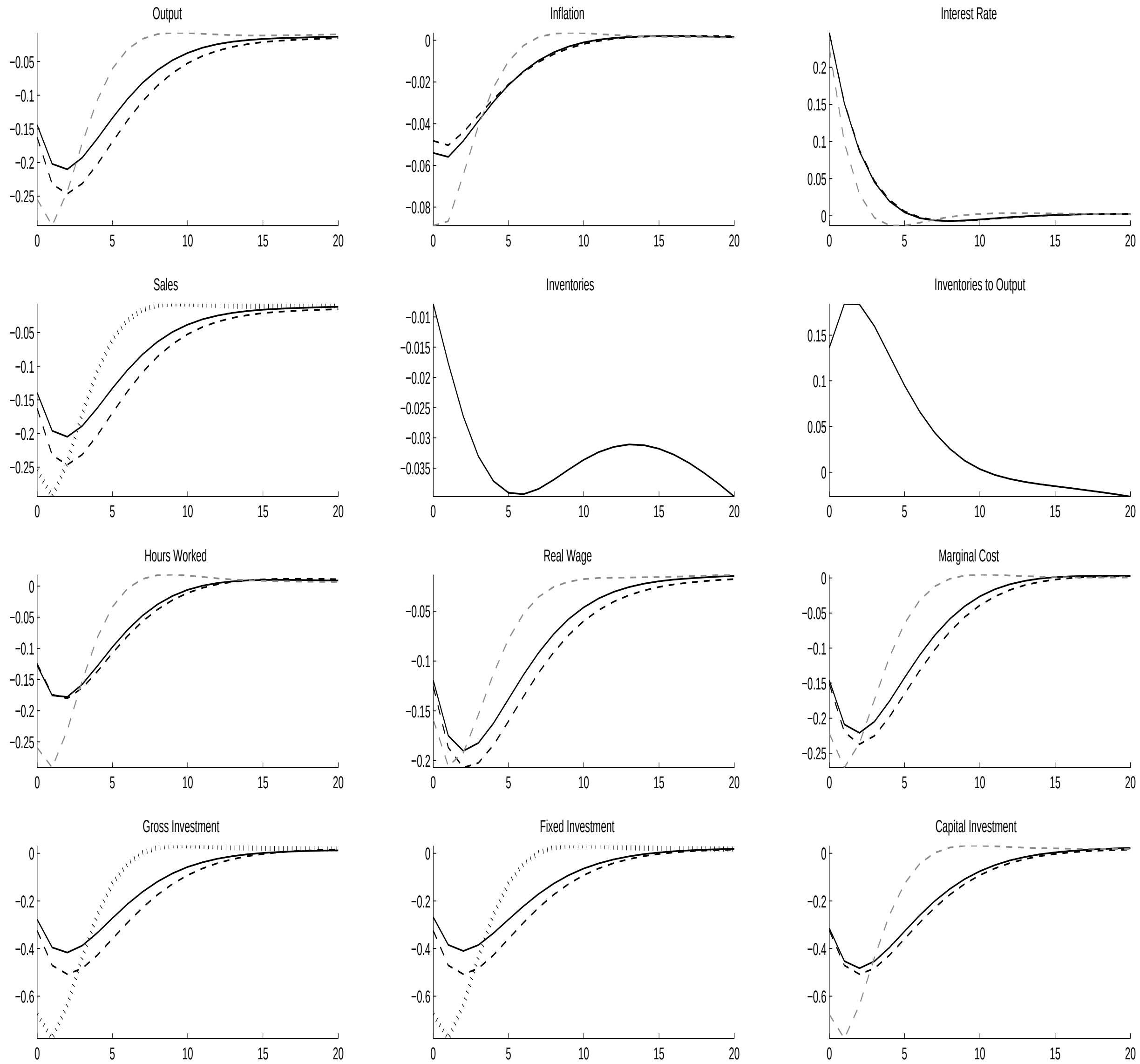
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 10. Counterfactual Responses to Capital Investment Shocks: Same Parameters



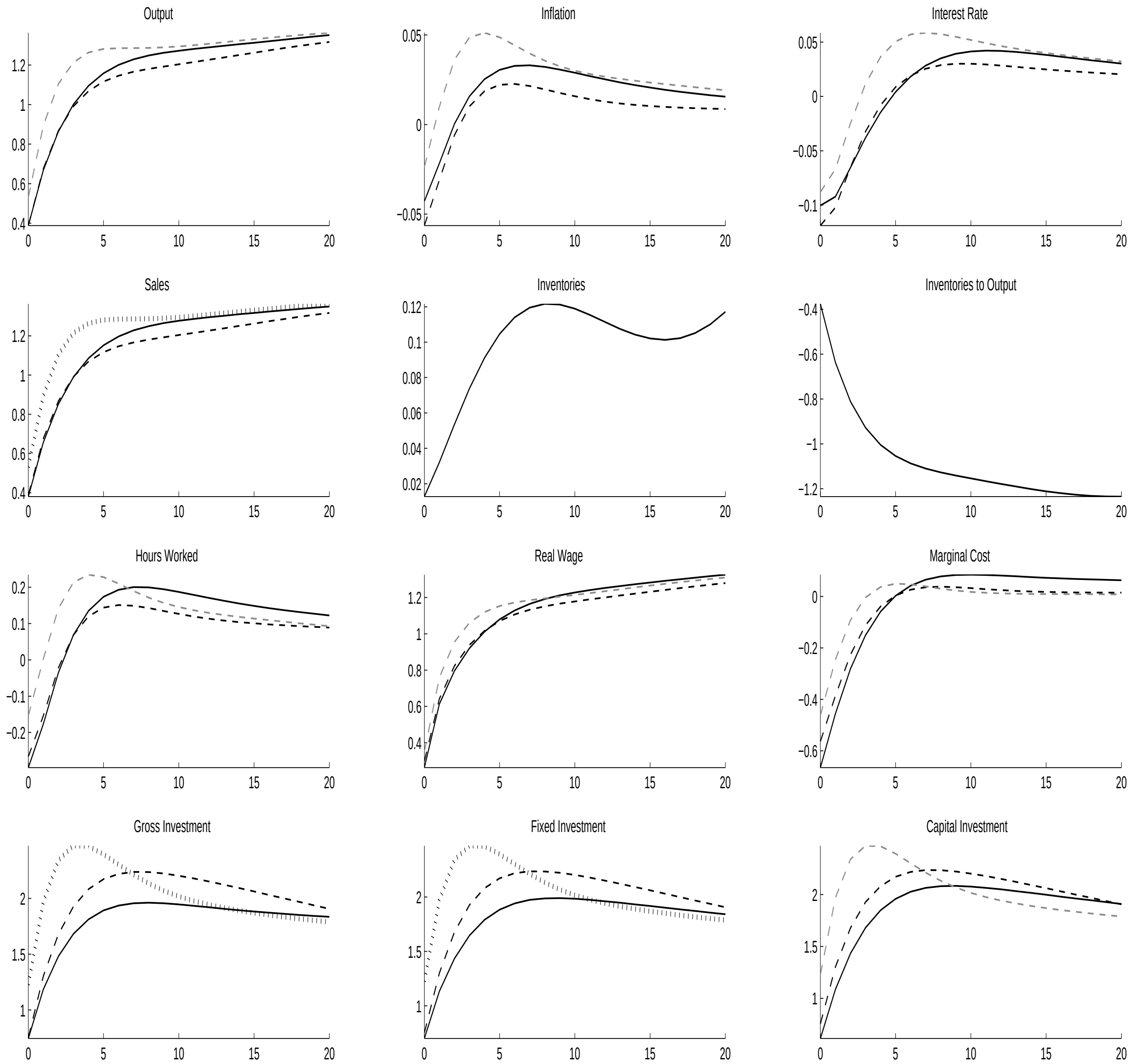
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 11. Counterfactual Responses to Monetary Policy Shocks: Same Parameters



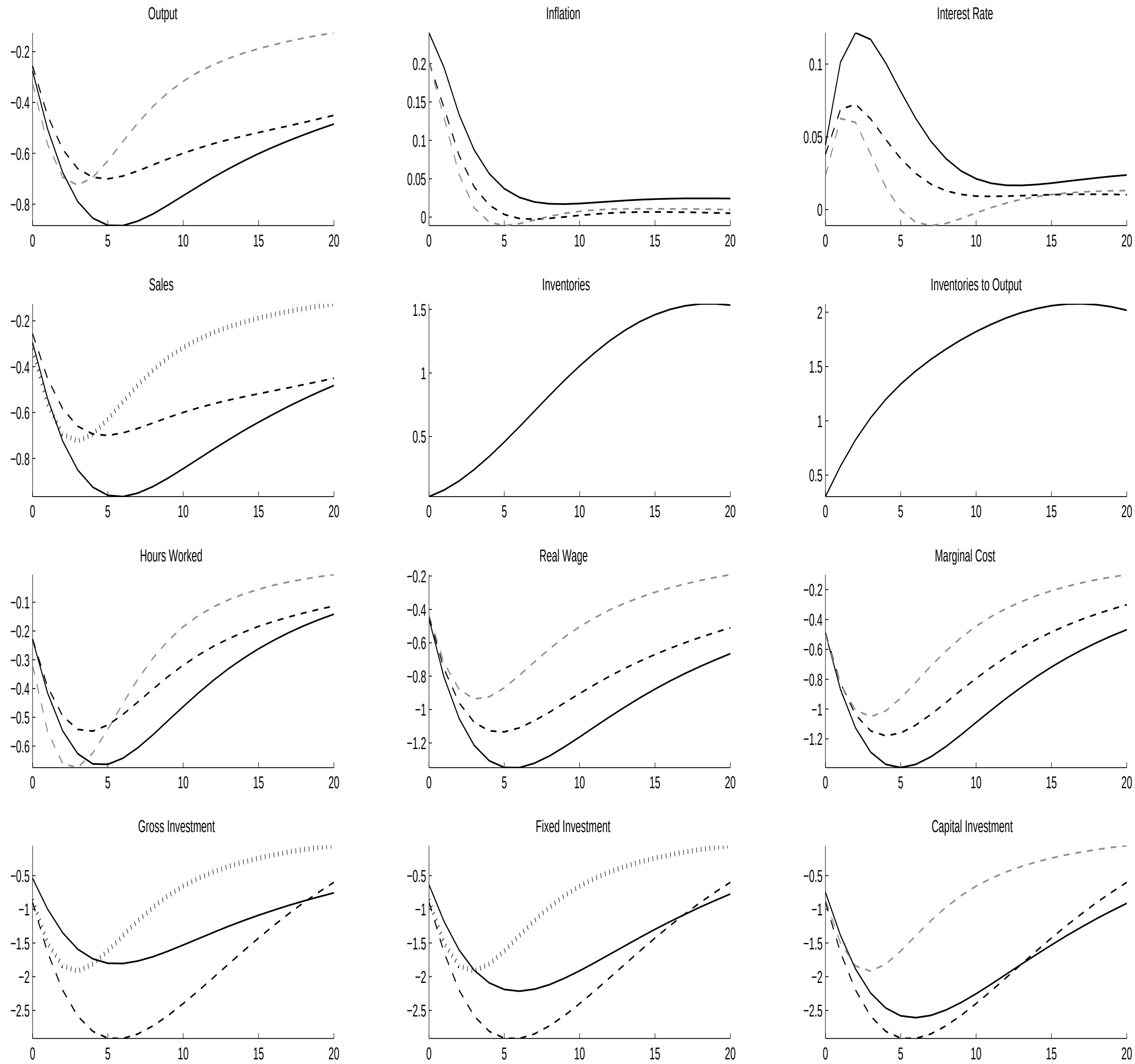
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 12. Counterfactual Responses to Technology Shocks: Same Data Set



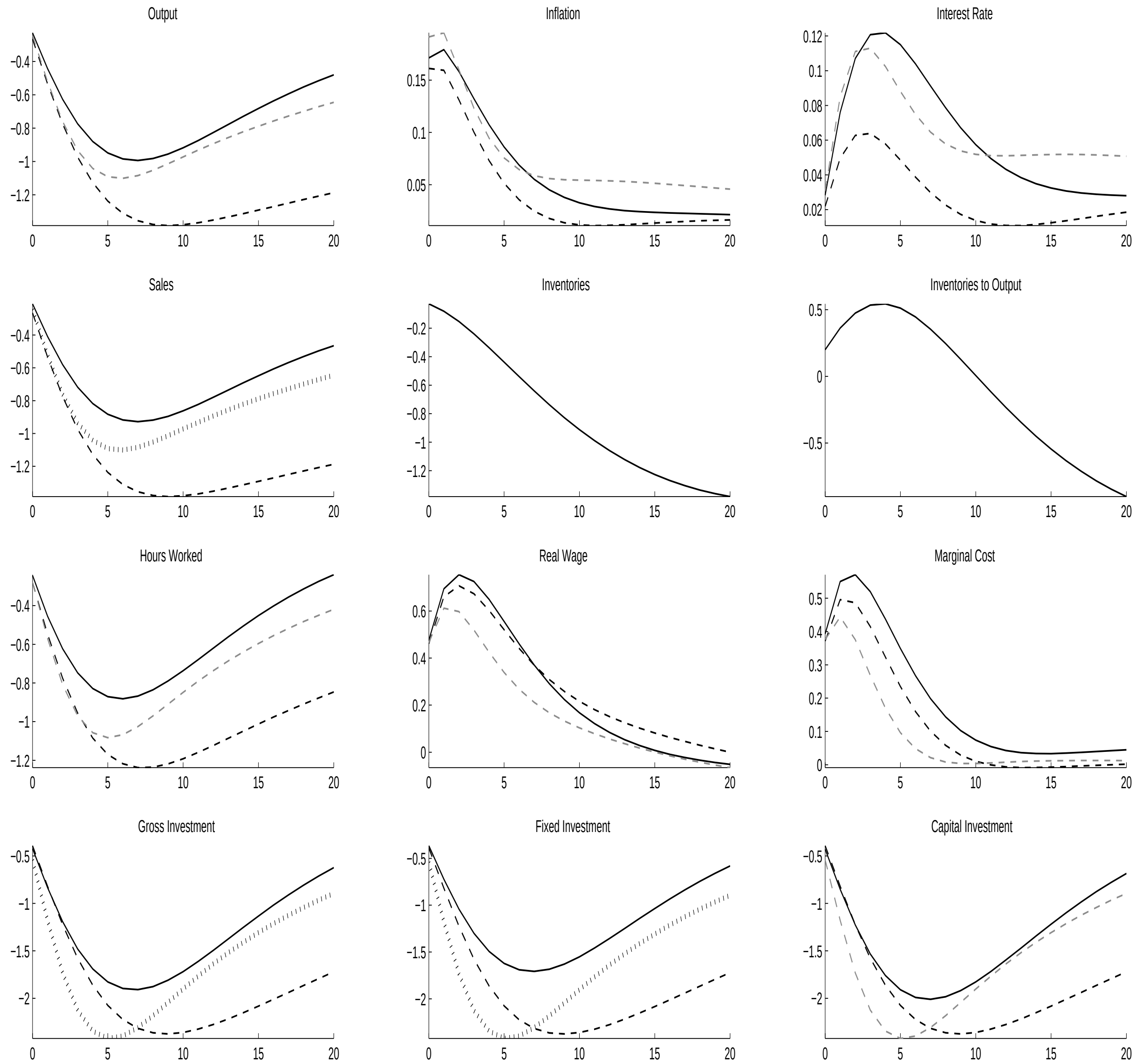
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 13. Counterfactual Responses to Price Markup Shocks: Same Data Set



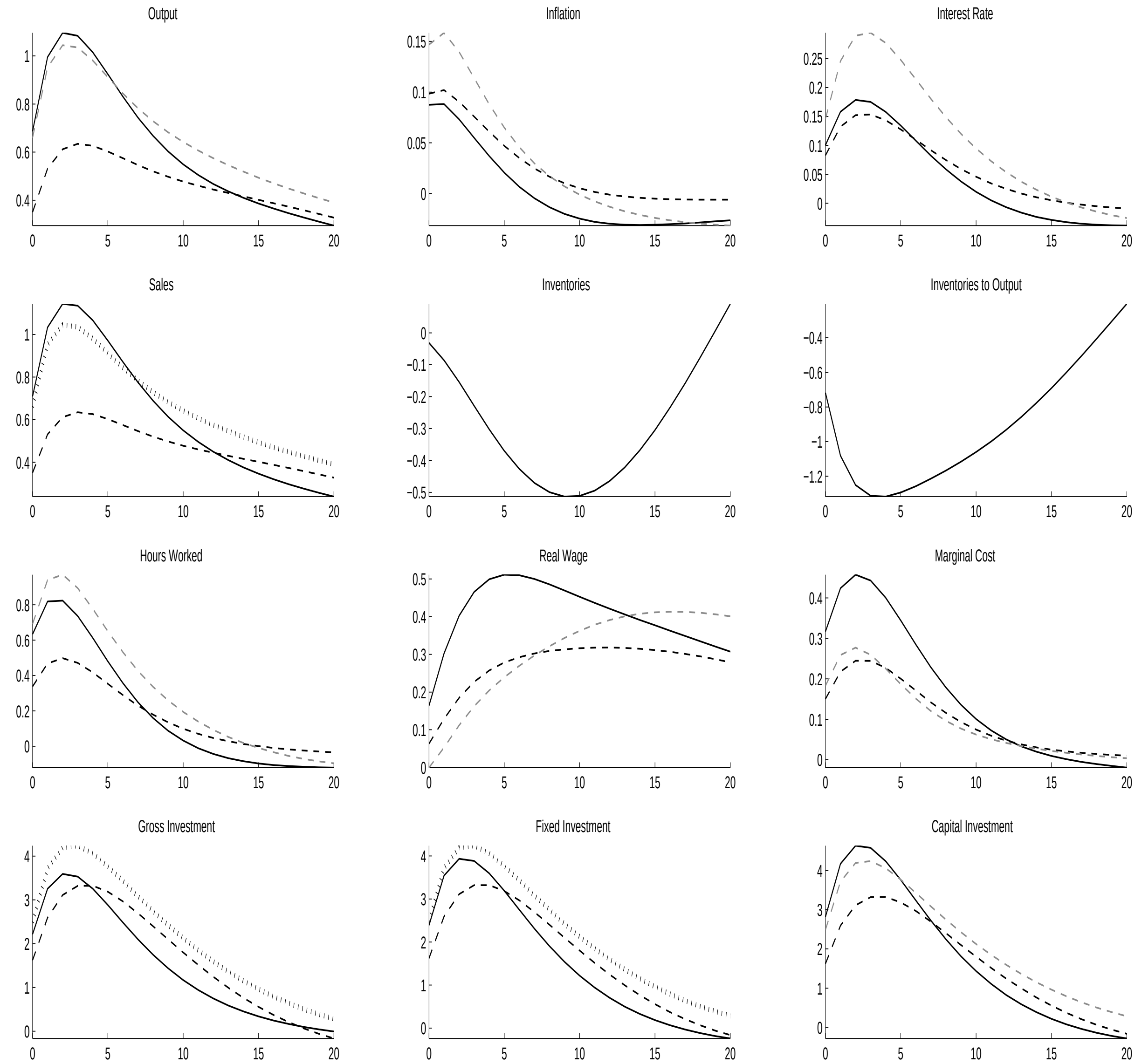
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 14. Counterfactual Responses to Wage Markup Shocks: Same Data Set



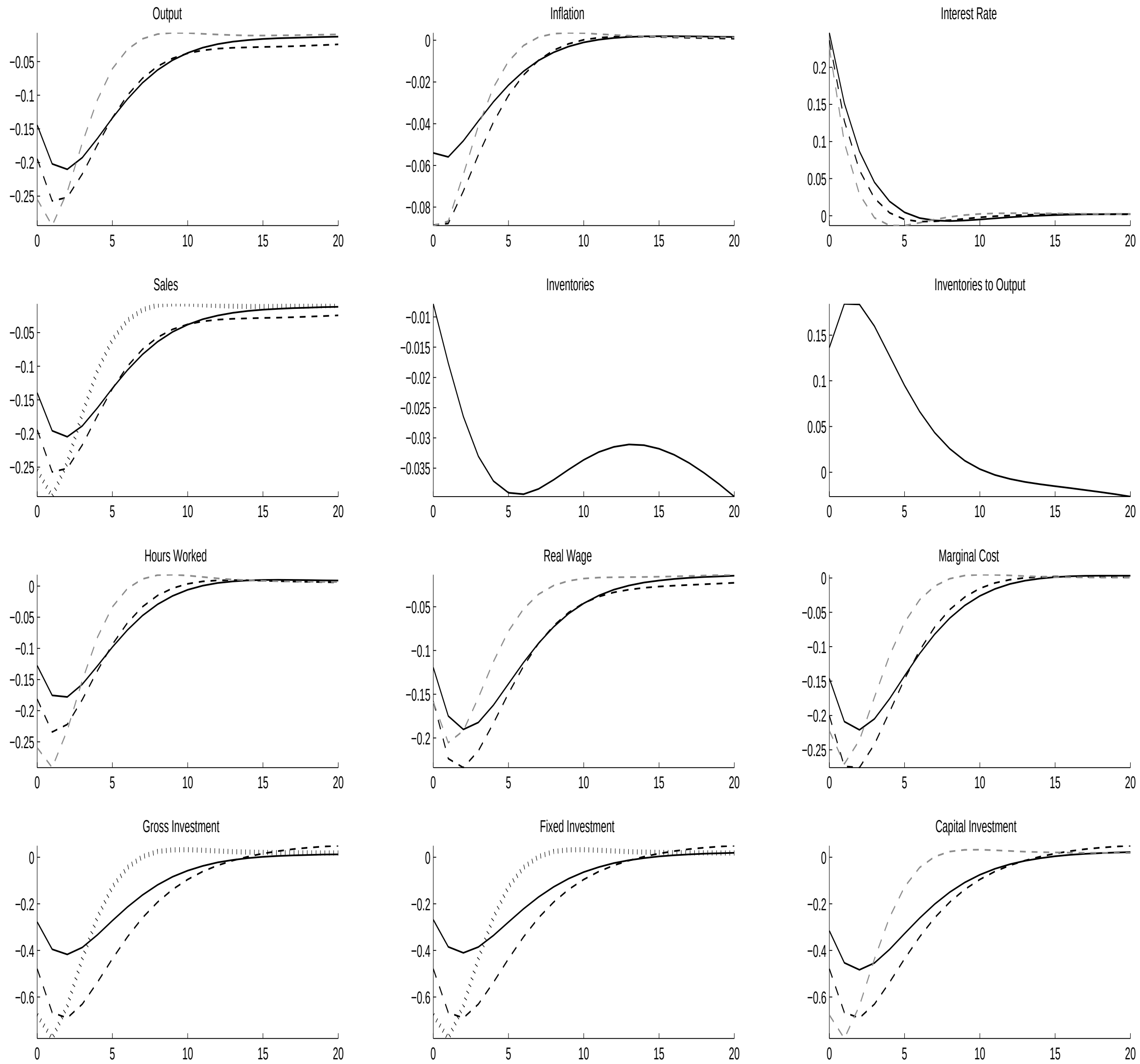
Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 15. Counterfactual Responses to Capital Investment Shocks: Same Data Set



Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).

Figure 16. Counterfactual Responses to Monetary Policy Shocks: Same Data Set



Simulated impulse responses for the model with inventories (solid lines) and without inventories (dashed gray lines) evaluated at the corresponding posterior mode. Dashed black lines show impulse responses for the model without inventories with parameter values for the posterior mode of the inventory model. Dotted lines show median response of the non-inventory model for output (sales) and capital investment (all investments).