

# What do inventories tell us about news-driven business cycles?\*

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## Abstract

There is widespread disagreement on the quantitative contribution of news shocks to business-cycle fluctuations. This paper provides a simple identifying restriction, based on inventory dynamics, that tightly pins down the contribution of news shocks to business-cycle volatility. We show that finished-good inventories must fall when there is an increase in consumption and investment induced by news shocks. A structural VAR with these sign restrictions indicates that news shocks account for at most 20 percent of output volatility. Since inventories comove positively with consumption and investment in the data, shocks that generate negative comovement cannot account for the bulk of fluctuations.

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# 1 Introduction

The sources of business cycles are an enduring subject of debate among macroeconomists. Recently, the literature has focused on news shocks — shocks that change agents’ expectations about future economic fundamentals, without affecting current fundamentals — as a potential driving force of aggregate fluctuations. Starting with [Beaudry and Portier \(2006\)](#), this literature has argued that news shocks may provide a good account of expansions and recessions, stressing episodes such as the US and Asian investment booms and busts of the late 1990s as examples.

In the news view of business cycles, booms and busts arise as a result of changes in expectations and investment ([Beaudry and Portier, 2013](#)). For example, when productivity is expected to increase in the future, investment increases today, in order to build up the capital stock and take advantage of lower future marginal costs. The boom in investment raises wages and hours worked, and the additional income leads to a consumption boom. Recent work has established the theoretical conditions under which business cycle models can successfully capture this mechanism. A prominent example is [Jaimovich and Rebelo \(2009\)](#), who show that, in a model with investment adjustment costs, variable capacity utilization, and weak wealth effects on hours worked, an expected rise in the marginal product of capital indeed leads to a boom in consumption, investment and output today.<sup>1</sup> With these elements, business cycle models can generate positive comovement of consumption, investment and output in response to shifts in expectations, making news shocks a plausible source of business-cycle fluctuations.

However, the literature has yet to come to a consensus regarding the quantitative importance of this type of shock. While some estimates suggest that they account for as much as 60 percent of output volatility, other equally plausible methods obtain numbers as low as 10 percent.<sup>2</sup> The goal of this paper is to use a new theoretical insight to pin down more precisely the contribution of news shocks to business-cycle volatility. Our innovation is to focus on a variable that is highly informative about news shocks, but so far has been neglected in the literature: investment in finished-good inventories.

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<sup>1</sup>Adding variable capacity and weak wealth effects on hours worked allows output to rise on impact and satisfy current demand, while investment adjustment costs force firms to smooth the desired increase in the stock of capital over time and start investing today.

<sup>2</sup>For example, [Beaudry and Portier \(2006\)](#) and [Schmitt-Grohé and Uribe \(2012\)](#) estimate that the contribution of news shocks to the business-cycle volatility of output is above 50 percent, while [Barsky and Sims \(2011\)](#) and [Khan and Tsoukalas \(2012\)](#) find much smaller numbers. This will be discussed in detail in later sections.

We focus on investment in finished-good inventories for two reasons. First, there is empirical evidence that finished-good inventories are a forward-looking variable that reflect changes in expectations about future economic conditions. For instance, [Kesavan, Gaur, and Raman \(2010\)](#) find that finished-good inventory data help improve forecasts of future sales. Second, finished-good inventories should react differently to changes that happen today and to changes that are expected to happen in the future. Temporary changes in productivity provide a straightforward illustration of this intuition. When productivity increases today, current income increases, so that sales rise. Additionally, firms bunch production today, in order to make the most out of the productivity increase. As a result, finished-good inventories also rise. Thus, when productivity changes today, sales and inventories should comove *positively*.<sup>3</sup> When productivity is expected to increase tomorrow, permanent income increases, which also leads to a rise in sales. However, since firms expect future production to be cheaper than current production, they satisfy this increase in sales not by producing more, but by depleting inventories. Thus, when productivity is expected to change tomorrow, sales and inventories should comove *negatively*. The sign of the comovement between sales and inventories should therefore help us distinguish between current and future expected changes in productivity.

In section 2, we start our analysis by introducing inventories into a news-driven business-cycle model. The inventory block of our model follows [Bils and Kahn \(2000\)](#). In section 3, we establish analytically that, in this model, good news about the future indeed lead to a boom in the components of private sales (consumption and investment), but a fall in inventories. The key mechanism that accounts for this result is similar to the intuition described above: news shocks cause agents to want to substitute production over time, and they are able to do so easily through inventory investment. With good news about the future, marginal cost is expected to be lower in the future than today. Optimal inventory investment behavior then dictates that firms should delay production, and satisfy current demand by drawing down on existing inventories.

In section 4, we show that this result survives a number of extensions of the baseline model. First, we show that the fall in inventories after a positive news shock is deep and protracted. Second, we establish that this result holds for other types of news, especially news about demand. Third, we show that the result survives the introduction of various types of adjustment costs, and

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<sup>3</sup>From now on, we will use the term “inventories” to indicate finished-good inventories when there is no confusion.

in particular adjustment costs to inventories. In section 5, we show that the result also holds in models with other microfoundations for inventory holding than those of [Bils and Kahn \(2000\)](#), such as the stockout-avoidance model of [Kahn \(1992\)](#), [Kryvtsov and Midrigan \(2013\)](#) and [Wen \(2011\)](#) or the (S,s) inventory model of [Khan and Thomas \(2007b\)](#). The strong intertemporal substitution channel with regards to news shocks is thus a general feature of inventory models.

Since structural models indicate that inventories and sales should comove negatively in response to news shocks, we use this prediction to pin down their quantitative contribution to business cycle volatility. In section 6, we describe a simple empirical strategy, based on a structural VAR with sign restrictions, that identifies shocks which generate negative comovement between inventories and sales. We find that these shocks explain less than 20 percent of the forecast error variance of output at business-cycle frequencies. The reason we get a small and precise contribution of news shocks is that, in the data, inventories and sales comove positively at those frequencies. Hence any shock that generates negative comovement between inventories and sales must have limited importance over the business cycle. In section 7, we show that the structural VAR results are consistent with results obtained using an estimated DSGE model with inventories. We estimate the model of [Schmitt-Grohé and Uribe \(2012\)](#) augmented with an inventory block, and using inventory data. This model includes a range of sources of news, and stationary as well as non-stationary shocks. Our median posterior estimate of the contribution of news shocks to the volatility of output is 17 percent. Section 8 concludes.

Our work relates to a number of papers that examine the behavior of investment in response to news shocks. [Jaimovich and Rebelo \(2009\)](#), [Christiano, Ilut, Motto, and Rostagno \(2008\)](#), as well as [Schmitt-Grohé and Uribe \(2012\)](#) document the importance of investment adjustment costs for news shocks to generate an immediate boom in investment and output. Inventory investment has been mostly neglected in this literature. One exception is [Vukotic \(2013\)](#), where inventories are introduced as a factor of production in the durable sector. Our approach is quite different from hers, since we examine inventories that are stored as finished goods. In her model, inventories play a role similar to investment. Our contribution to the news literature is to illustrate a new channel through which news shocks operate – the intertemporal substitution channel – by focusing on the investment behavior of finished-good inventories, a form of investment that is distinct from investment in fixed capital.

Our work also relates to the recent literature on inventories that matches their stylized business-cycle behavior using micro-founded models. These models differ in the reason for which firms hold inventories, aside from shifting production over time. One branch of the literature argues that inventories exist in order to facilitate sales, either by their use for displaying and advertising purposes (Bils and Kahn, 2000), or because they can be used as a buffer against stockouts (Wen, 2011; Kryvtsov and Midrigan, 2013). Another branch of the literature argues that inventories exist due to bunching behavior induced by fixed ordering costs (Fisher and Hornstein, 2000; Khan and Thomas, 2007b). Since our focus is on finished-good inventories, we follow more closely the former approach.<sup>4</sup> Nevertheless, the key theoretical result of the paper also applies to the latter approach, since a common feature of all these models is that inventories are producers' means of substituting production over time. Our contribution to this literature is to highlight this common mechanism, and draw its implications for business-cycle comovement in the context of news shocks.

Finally, our empirical approach is based on the literature on sign restrictions in a VAR framework. Sign restrictions have been used to identify monetary policy shocks (Faust, 1998; Uhlig, 2005), fiscal policy shocks (Mountford and Uhlig, 2008; Caldara and Kamps, 2012), and also news shocks (Beaudry, Nam, and Wang, 2011).

## 2 A finished-good inventory model

In this section, we describe a general equilibrium model of inventory dynamics based on the work of Pindyck (1994), Bils and Kahn (2000), and Jung and Yun (2006). The tractability of this model delivers clear intuitions on the response of inventories to news shocks. Other inventory models will be discussed in later sections.

The key feature of the so-called “stock-elastic” demand model of this section is the assumption that sales of a firm are elastic to the amount of goods available for sale, which we term “on-shelf goods.” This assumption finds empirical support for many categories of goods, as documented by Pindyck (1994) or Copeland, Dunn, and Hall (2011). The positive elasticity of sales to on-shelf goods captures the idea that with more on-shelf goods, customers are more likely to find a good match and purchase the product.

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<sup>4</sup>See Khan and Thomas (2007a) for a comparison of the two approaches.

## 2.1 Description of the stock-elastic demand model

The economy consists of a representative household and monopolistically competitive firms. The output of the firms are storable goods, of which they keep a positive inventory. We start with the household problem.

**Household problem** A representative household maximizes the following expected sum of discounted utility,

$$E_0 \left[ \sum_{t=0}^{\infty} \beta^t U(c_t, n_t; \psi_t) \right], \quad (1)$$

where  $c_t$  is the consumption of the final good,  $n_t$  denotes the supply of labor services, and  $\psi_t$  is a exogenous variable that introduces a wedge between the marginal rate of substitution between consumption and leisure, and the real wage, and which we call a “labor wedge” shock. We assume that the household’s period utility function takes the form proposed by [Greenwood, Hercowitz, and Huffman \(1988\)](#), henceforth GHH):

$$U(c, n; \psi) = \frac{1}{1 - \sigma} \left( c - \psi \frac{n^{1+\xi^{-1}}}{1 + \xi^{-1}} \right)^{1-\sigma},$$

where  $\xi$  is the Frisch elasticity of labor supply and  $\sigma$  denotes the inverse of the elasticity of the household’s intertemporal substitution. This preference specification has been widely used in the literature on news shocks, and it implies zero wealth effects on labor supply.

The household’s maximization problem is subject to the following constraints:

$$\int_0^1 p_t(j) s_t(j) dj + \mathbb{E}_t [Q_{t,t+1} B_{t+1}] \leq W_t n_t + R_t k_t + \int_0^1 \pi_t(j) dj + B_t, \quad (2)$$

$$k_{t+1} = i_t \left[ 1 - \phi \left( \frac{i_t}{i_{t-1}} \right) \right] + (1 - \delta_k) k_t, \quad (3)$$

$$c_t + i_t \leq x_t. \quad (4)$$

Equation (2) is the household budget constraint. The household earns income each period by providing labor  $n_t$  at a given wage  $W_t$ , lending capital  $k_t$  at a rate  $R_t$ , claiming the profit  $\pi_t(j)$  from each firm  $j \in [0, 1]$ , and receiving bond payments  $B_t$ . It spends its income in purchases of each

variety in the amount  $s_t(j)$  at a price  $p_t(j)$ , and in purchases of the state-contingent one-period bonds  $B_{t+1}$ . The probability-adjusted price of each of these bonds is  $Q_{t,t+1}$ , for each state in period  $t + 1$ .

Equation (3) is the law of motion of capital with adjustment costs to investment. The adjustment cost function  $\phi(\cdot)$  is twice-differentiable, with  $\phi(1) = \phi'(1) = 0$  and  $\phi''(1) > 0$ . When firms' desired future level of capital is high, this type of adjustment cost forces them to smooth out the desired increase over time and start investing today.

Equation (4) states that the household's consumption and investment cannot exceed its total absorption of final goods,  $x_t$ , which is constructed by aggregating their purchase of intermediate goods  $\{s_t(j)\}_{j \in [0,1]}$ . The aggregation of the intermediate goods  $\{s_t(j)\}_{j \in [0,1]}$  into  $x_t$  is given by a Dixit-Stiglitz type aggregator of the form:

$$x_t = \left( \int_0^1 v_t(j)^{\frac{1}{\theta}} s_t(j)^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}}, \quad (5)$$

where  $v_t(j)$  is the taste-shifter for each product  $j$  and  $\theta$  is the elasticity of substitution across intermediate goods. It follows from expenditure minimization that the demand function for each good and the aggregate price level take the following forms:

$$s_t(j) = v_t(j) \left( \frac{p_t(j)}{P_t} \right)^{-\theta} x_t, \quad P_t = \left( \int_0^1 v_t(j) p_t(j)^{1-\theta} dj \right)^{\frac{1}{1-\theta}}.$$

In the stock-elastic demand model, the taste shifter for variety  $j$  is assumed to depend on the amount of goods on shelf proposed by the firm producing variety  $j$ ,  $a_t(j)$ , in the following fashion:

$$v_t(j) = \left( \frac{a_t(j)}{a_t} \right)^\zeta, \quad (6)$$

where the normalization by  $a_t$ , defined as the the economy-wide average of on-shelf goods, ensures that the mean of  $\nu_t(j)$  across goods is equal to 1. The parameter  $\zeta > 0$  controls the degree of the shift in taste due to the relative amount of goods on-shelf.

Finally, the household is given an initial level of capital  $k_0$  and bonds  $B_0$ , and its optimization problem is subject to a no-Ponzi condition for both capital and stage-contingent bond holdings.

**Firm problem** Each monopolistically competitive firm  $j \in [0, 1]$  maximizes the expected discounted sum of profits

$$E_0 \left[ \sum_{t=0}^{\infty} Q_{0,t} \pi_t(j) \right], \quad (7)$$

where

$$\pi_t(j) = p_t(j)s_t(j) - W_t n_t(j) - R_t k_t(j). \quad (8)$$

Note that the profit in each period is the revenue from sales net of the cost from hiring labor  $n_t(j)$  and renting capital  $k_t(j)$  at their respective prices  $W_t$  and  $R_t$ . The term  $Q_{0,t}$  is the discount factor of between period 0 and  $t$ , so that  $Q_{0,t} = \prod_{T=0}^{t-1} Q_{T,T+1}$ . This discount factor is consistent with households being the final owners of firms. The firm faces the following constraints:

$$a_t(j) = (1 - \delta_i) \text{inv}_{t-1}(j) + y_t(j), \quad (9)$$

$$\text{inv}_t(j) = a_t(j) - s_t(j), \quad (10)$$

$$y_t(j) = z_t k_t^{1-\alpha}(j) n_t^\alpha(j), \quad (11)$$

$$s_t(j) = \left( \frac{a_t(j)}{a_t} \right)^\zeta \left( \frac{p_t(j)}{P_t} \right)^{-\theta} x_t. \quad (12)$$

Equation (9) is the inventory stock accumulation equation. The stock (on-shelf goods) of the firm,  $a_t(j)$ , consists of the undepreciated stock of inventories from the previous period  $(1 - \delta_i) \text{inv}_{t-1}(j)$  and of current production  $y_t(j)$ . The parameter  $\delta_i$  denotes the depreciation rate of inventories. Equation (10) states that on-shelf goods that are unsold are accounted as inventories.<sup>5</sup> Equation (11) is the production function. Firms use a constant returns to scale production function, with capital and labor as inputs. The variable  $z_t$  represents total factor productivity and is exogenous. Finally, monopolistically competitive firms face the demand function (12) stemming from the household problem.

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<sup>5</sup>In the data, this is recorded as the end-of-period inventory stock in each period.



**Market clearing** Labor and capital markets clear, and net bond holdings is zero:

$$n_t = \int_0^1 n_t(j) dj, \quad (13)$$

$$k_t = \int_0^1 k_t(j) dj, \quad (14)$$

$$B_{t+1} = 0. \quad (15)$$

Sales of goods for each variety  $j$  also clears, as is implicit in the expression of the demand function (12). The average level of on-shelf goods in the economy  $a_t$  is defined by:

$$a_t = \int_0^1 a_t(j) dj. \quad (16)$$

## 2.2 Equilibrium

A market equilibrium of this economy is defined as follows.

**Definition 1 (Market equilibrium of the stock-elastic demand model)** *A market equilibrium of the stock-elastic demand model is a set of stochastic processes for aggregate variables*

$$c_t, n_t, k_{t+1}, i_t, B_{t+1}, x_t, a_t, W_t, R_t, P_t, Q_{t,t+1},$$

*and firm-level variables*

$$\{a_t(j)\}, \{n_t(j)\}, \{k_t(j)\}, \{v_t(j)\}, \{s_t(j)\}, \{y_t(j)\}, \{inv_t(j)\}, \{p_t(j)\},$$

*such that, given the exogenous stochastic processes  $z_t$ ,  $\psi_t$ , as well as initial conditions  $k_0$ ,  $B_0$  and  $\{inv_{-1}(j)\}$ :*

- *households maximize (1) subject to (2) - (6) and a no-Ponzi condition,*
- *each firm  $j \in [0, 1]$  maximizes (7) subject to (8) - (12),*
- *markets clear according to (13) - (16).*

The two exogenous processes in our economy are total factor productivity  $z_t$  and the labor wedge  $\psi_t$ . The news component to these two shocks are the primary contributors to aggregate

fluctuations in [Schmitt-Grohé and Uribe \(2012\)](#).<sup>6</sup>

### 2.3 The optimal choice of inventories

The full set of equilibrium conditions are provided in appendix [A](#). A market equilibrium of the stock-elastic demand model is symmetric, so that  $a_t(j) = a_t$ ,  $s_t(j) = s_t$ ,  $inv_t(j) = inv_t$ ,  $y_t(j) = y_t$ , and  $p_t(j) = p_t$  for all  $j$ . Here, we discuss the optimal stock choice of firms.

In the market equilibrium, marginal cost is the real wage divided by the marginal product of labor:

$$mc_t = \frac{W_t/P_t}{\alpha z_t (k_t/n_t)^{1-\alpha}}. \quad (17)$$

Using this, the optimal stock choice of firms is governed by the equation:<sup>7</sup>

$$mc_t = \frac{\partial s_t}{\partial a_t} + \left(1 - \frac{\partial s_t}{\partial a_t}\right) \mathbb{E}_t[q_{t,t+1}(1 - \delta_i)mc_{t+1}]. \quad (18)$$

The left hand side of this equation represents the cost of adding an extra unit of goods to the stock of goods on sale,  $a_t$ , which equals the current marginal cost of production. The right hand side represents the two benefits of adding this extra unit. First, by producing and stocking an extra unit, the firm is able generate an additional fraction  $(\partial s_t/\partial a_t)$  of sales. Second, since some of the extra goods stocked will not be sold and will be stored as inventories for the next period, future production costs are reduced.

It is important to notice that at the nonstochastic steady state of the economy, the stock of inventories is positive. Since the real interest rate and the inventory depreciation rate are both positive at the steady state, holding inventories is costly. However, consistent with the first term on the right hand side of [\(18\)](#), there is a convenience yield associated with holding a positive amount of inventories in each period. In the model, the convenience yield is the additional sales created by holding a positive level of stock. Therefore, there will be a positive amount of inventories in steady state, despite the intertemporal costs that holding inventories implies.

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<sup>6</sup>Other types of shocks will be discussed in later sections.

<sup>7</sup>Here,  $q_{t,t+1} = Q_{t,t+1}P_{t+1}/P_t$  denotes the real stochastic discount factor of the household.

Rearranging, (18) can be expressed as:

$$\frac{\partial s_t}{\partial a_t} = \frac{\gamma_t^{-1} - 1}{\mu_t - 1}, \quad (19)$$

where:

$$\mu_t \equiv \frac{1}{(1 - \delta_i)\mathbb{E}_t[q_{t,t+1}mc_{t+1}]}, \quad \gamma_t \equiv (1 - \delta_i)\mathbb{E}_t\left[\frac{q_{t,t+1}mc_{t+1}}{mc_t}\right].$$

The variable  $\mu_t$  is the markup of price over expected discounted marginal cost. This is the relevant markup concept in an economy where firms produce to stock: indeed, the true cost of sales is not current but future marginal cost, since selling an extra unit reduces tomorrow's stock of goods. The variable  $\gamma_t$  is the expected discounted growth rate of marginal cost, which summarizes the firm's opportunity cost of producing today. The optimal stocking behavior of a firm balances these 3 margins: markup, discounted growth rate of marginal cost, and additional sales generated by extra inventory holdings.

In equilibrium, the optimal choice of inventories can be approximated up to first order as:<sup>8</sup>

$$\widehat{inv}_t = \hat{s}_t + \eta\hat{\gamma}_t,$$

where hatted variables represent log-deviations from its steady-state. This condition states that two factors determine the dynamics of inventories.

First,  $\hat{s}_t$  represents the demand channel: firms in this economy build up their inventories when sales are high. For example, when there is an increase in aggregate demand, firms make the most out of it by stocking more goods on shelf to generate additional sales. However, since the additional unit on stock will not lead to a full amount of realized sales, (end-of-period) inventories also increase.

Second,  $\eta\hat{\gamma}_t$  represents the intertemporal substitution channel, where  $\eta > 0$  is a combination of structural parameters that will be specified in proposition 1. Intuitively,  $\eta$  captures the degree of intertemporal substitution of production in this economy. For example, when there is an increase in future expected discounted marginal cost relative to current marginal cost, then  $\hat{\gamma}_t$  is positive and firms will increase their inventories. This happens because firms realize that it is cheaper to produce today than in the future and they now bunch their production today and store more inventories.

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<sup>8</sup>This equation is derived by combining (10), (19) and the optimal pricing condition  $\hat{\mu}_t = 0$ .

When the value of  $\eta$  is large, then the degree of intertemporal substitution is such that even a small change in the perception of the marginal cost will result in a large change in inventories.

Thus, in this model, changes in inventories are governed by the relative strength of the demand channel and the intertemporal substitution channel.

### 3 The impact effect of news shocks

We now turn to studying the effect of news shocks in this model economy. In this section, we focus on impact responses. We derive analytical conditions under which news shocks result in positive comovement on impact between sales and inventories, assess whether those conditions are likely to hold in reasonable calibrations of the model, and inspect the mechanisms underpinning the result.

#### 3.1 A log-linearized framework

We analyze a first-order log-linear approximation of the model around its steady-state. The following framework summarizes the equilibrium conditions needed for the purpose of our subsequent analysis.

**Proposition 1 (Stock-elastic demand model)** *On impact and with only news shocks, so that  $\hat{z}_t = 0$  and  $\hat{\psi}_t = 0$ , the following equations represent the log-linearized market equilibrium of definition 1:*

$$\widehat{mc}_t = \omega \hat{y}_t, \tag{20}$$

$$\kappa \hat{y}_t = \hat{s}_t + \frac{\kappa - 1}{\delta_i} [\widehat{inv}_t - (1 - \delta_i) \widehat{inv}_{t-1}], \tag{21}$$

$$\widehat{inv}_t = \hat{s}_t + \tau \hat{\mu}_t + \eta \hat{\gamma}_t, \tag{22}$$

$$\hat{\mu}_t = 0, \tag{23}$$

$$\hat{\mu}_t + \hat{\gamma}_t + \widehat{mc}_t = 0. \tag{24}$$

*The mapping from the structural model parameters to the parameters of the reduced-form equations*

is given by:

$$\omega = \frac{1 + (1 - \alpha)\xi}{\alpha\xi}, \quad (25)$$

$$\kappa = 1 + \delta_i IS, \quad (26)$$

$$\eta = \frac{1 + IS}{IS} \frac{1}{1 - \beta(1 - \delta_i)}, \quad (27)$$

$$\tau = \theta \frac{1 + IS}{IS},$$

where  $IS$  is the steady-state inventory-sales ratio, given by

$$IS = \frac{(\theta - 1)(1 - \beta(1 - \delta_i))}{\zeta\beta(1 - \delta_i) - (\theta - 1)(1 - \beta(1 - \delta_i))}.$$

Equation (20) relates marginal cost to output, which is derived by combining the labor supply and demand conditions, and the production function. Importantly, this equation is not connected to the introduction of inventories in our model. With  $\omega > 0$ , the equation states that real marginal cost increases with output. The parameter  $\omega$  is the elasticity of marginal cost with respect to output, keeping constant total factor productivity. In other words,  $\omega$  represents the degree of decreasing returns in the economy due to predetermined capital in the short run (represented by  $\alpha$ ) and the disutility of labor supply (represented by  $\xi$ ). The value of  $\omega$  itself has been at the center of debate in the monetary economics literature, and there is disagreement about its magnitude. [Woodford \(2003\)](#) contrasts two values of  $\omega$ : 1.25, from [Chari, Kehoe, and McGrattan \(2000\)](#), and 0.47, from [Rotemberg and Woodford \(1997\)](#). Moreover, [Dotsey and King \(2006\)](#) suggest a lower bound of 0.33 for  $\omega$ . A conservative lower bound for  $\omega$  is thus:

$$\omega \geq 0.3.$$

Equation (21) is the law of motion for the stock of inventories, obtained from combining equations (9) and (10). This law of motion states that output should equal sales plus inventory investment. The parameter  $\kappa$  in (21) denotes the steady-state output to sales ratio. In NIPA, the time

series average of inventory investment over output is around 0.5 percent, so that:

$$\kappa = 1.005.$$

Equations (22) and (23) are the optimal stocking and pricing conditions, respectively. Combining these two equations, we see that inventories are determined by the demand channel ( $\hat{s}_t$ ) and the intertemporal substitution channel ( $\eta\hat{\gamma}_t$ ), as we discussed in section 2. Here we focus on the numerical value of  $\eta$ , the degree of intertemporal substitution in production. Equation (27) indicates that a lower bound for  $\eta$  is  $(1 - \beta(1 - \delta_i))^{-1}$ . The lower bound depends on two parameters,  $\beta$  and  $\delta_i$ . First, the household discount factor  $\beta$  governs the opportunity cost of holding inventories. In the limiting case where  $\beta = 1$ , there is no opportunity cost of holding inventories since the real interest rate  $1/\beta - 1$  is 0. Second, the depreciation rate of inventories  $\delta_i$  represent the physical cost of holding inventories. Therefore, the value  $1 - \beta(1 - \delta_i)$  represents the overall intertemporal cost of adjusting inventories. In the limiting case where both the opportunity cost and the physical cost of inventories are zero, then the lower bound of  $\eta$  is infinity. At quarterly frequency, we set  $\beta = 0.99$ , which is standard. For  $\delta_i$ , the logistics literature estimates the carrying cost to be around 12–15 percent in annual terms.<sup>9</sup> With a rather high value of  $\delta_i = 0.04$ , the lower bound is thus:

$$\eta > 20.$$

Lastly, equation (24) follows from the definition of  $\mu_t$  and  $\gamma_t$  in section 2.

### 3.2 The impact response of inventories to good news about the future

Given sales  $\hat{s}_t$ , equations (20) - (24) relate the following four variables: output  $\hat{y}_t$ , inventories  $i\hat{n}v_t$ , the discounted growth rate of marginal cost  $\hat{\gamma}_t$ , and markups  $\hat{\mu}_t$ . We adopt the following definition of a news shock in the context of this reduced-form framework: a news shock is a shock that has no impact on current fundamentals ( $\hat{z}_t = 0$  and  $\hat{\psi}_t = 0$ ), but which changes expectations about future fundamentals ( $\mathbb{E}_t\hat{z}_{t+k} \neq 0$  or  $\mathbb{E}_t\hat{\psi}_{t+k} \neq 0$  for some  $k > 0$ ).

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<sup>9</sup>The overall carrying cost suggested in the literature is on average 25 percent in annual terms (Stock and Lambert, 2001). However, these include interest payments and clerical costs of managing inventories. Excluding those costs gives our numbers.

**Proposition 2 (The impact response of inventories to a good news about the future)**

*When news arrive, inventories and sales positively comove on impact if and only if:*

$$\eta < \frac{\kappa}{\omega}.$$

This proposition indicates that the positive comovement between inventories and sales only depends on the three parameters discussed above,  $\kappa$ ,  $\omega$  and  $\eta$ . With  $\kappa = 1.005$ , the two parameters  $\omega$  and  $\eta$  need to be sufficiently small for there to be positive comovement between inventories and sales on impact.. Following our previous discussion on numerical values, a conservative upper bound on  $\kappa/\omega$  is 3.3. However, given that our lower bound of  $\eta$  with a large carrying cost of inventories is still 20, the condition of proposition 2 is not met and in fact fails by an order of magnitude. Thus, our framework indicates that following the arrival of good news about the future, the boom in sales associated to a news shock is accompanied by a fall in inventories. In other words, there is negative comovement between inventories and sales in response to news shocks.

### 3.3 Discussion

The numerical discussion of proposition 2 concludes that inventories must fall when good news about the future generates a current boom in sales. The two key parameters that drive this result are  $\omega$  and  $\eta$ .

First, when  $\omega$  is small, then a sales boom will also correspond to an inventory boom. This is because with a small  $\omega$ , marginal cost barely responds to changes in the level of output produced by firms. Therefore, intertemporal substitution in production is less attractive for firms. In this case, inventories are mostly used to affect demand, and with a sufficient increase in demand, firms will optimally accumulate inventories.

Second, when  $\eta$  is small, the intertemporal substitution channel itself becomes weak. This is the case when the firm faces large costs in storing goods for the future. When the interest rate is high or the depreciation of inventories are high, then it is costly for firms to hold inventories. In this economy, even though marginal cost may respond sensitively to production, firms will be less willing to smooth this out by adjusting inventories. Therefore a sufficient increase in demand will also lead to an accumulation of inventories.

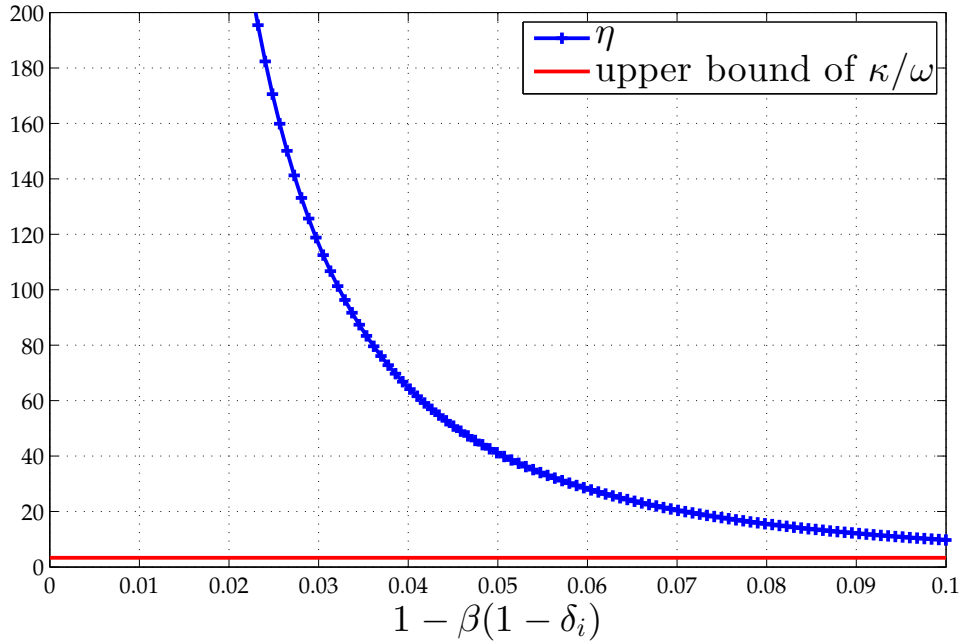


Figure 1: Value of  $\eta$  as a function of  $1 - \beta(1 - \delta_i)$ . Stock-elastic demand model; holding fixed all the other structural parameters.

To be more precise on this connection between  $\eta$  and the cost of storing goods, recall that the lower bound of  $\eta$  is negatively related to the intertemporal cost of adjusting inventories,  $1 - \beta(1 - \delta_i)$ . In fact, we also find that the value of  $\eta$  itself is negatively related with the intertemporal cost. In figure 1, we fix the other structural parameters and change the value of  $1 - \beta(1 - \delta_i)$  to show this relation.<sup>10</sup> In the extreme case with zero intertemporal cost of adjusting inventories, we see that the degree of intertemporal substitution,  $\eta$ , reaches infinity. With higher intertemporal cost imposed, the value of  $\eta$  becomes smaller, but far from satisfying the positive comovement condition of proposition 2 even for the upper bound of  $\kappa/\omega$ , which is 3.3 (the horizontal line on the graph).

## 4 Dynamic analysis

The analysis of the previous section focused on the impact responses to news shocks, in an effort to understand forces underlying the joint response of inventories and sales to news shocks. We found that news shocks generate negative comovement between inventories and sales. We now

<sup>10</sup>The value of  $\eta$  is a function of  $\beta$  and  $\delta_i$  only in the form of  $1 - \beta(1 - \delta_i)$ . Hence there is no need to consider  $\beta$  and  $\delta_i$  separately.



Parameter	Value	Description
$\beta$	0.99	Subjective discount factor
$\sigma$	1	Inverse elasticity of household intertemporal substitution
$\delta_k$	0.025	Depreciation rate of capital
$\phi''(1)$	9.11	Investment adjustment costs
$\xi$	2.5	Frisch elasticity of labor supply
$\psi$	6.72	Steady-state hours worked = 0.2
$\alpha$	0.67	Labor elasticity of production function
$\theta$	5	Elasticity of substitution across intermediate goods
$\delta_i$	0.025	Depreciation rate of inventories
$\zeta$	0.25	Steady-state inventory-sales ratio = 0.75
$\rho_z$	0.99	Persistence of the productivity process
$\rho_\psi$	0.95	Persistence of the labor wedge process

Table 1: Calibration of the stock-elastic demand model.

turn to several extensions of this result. We first show that the negative comovement between inventories and sales holds beyond impact, and we establish that introducing variable capacity utilization (which allows output to increase in the short run) does not overturn our result. Second, we study the response of inventories to surprise (non-news) shocks, and confirm that the negative comovement property is an identifying feature of news shocks. Third, we analyze whether news about other fundamentals than productivity or the labor wedge, in particular about news about demand, also generate negative comovement between inventories and sales. Fourth, we check the robustness of our result by introducing different types of adjustment costs to inventories.

Since the analysis will be numerical, we start with a brief discussion on the calibration of the model.

## 4.1 Calibration

The calibration which we use in this section is summarized in table 1. Standard model parameters are calibrated using estimates from the business-cycle literature. Parameters specific to the inventory blocks of the models are calibrated to match sample averages of the inventory-sales ratio. For the exogenous variables we assume that the realization of these shocks follow AR(1) processes. For the persistence of the shocks, we assume that  $\rho_z = 0.99$  and  $\rho_\psi = 0.95$ .

Our calibration implies that  $\eta = 67.15$ ,  $\omega = 1.09$  and  $\kappa = 1.02$ , so that applying proposition 2, inventories respond negatively to news shocks on impact.

## 4.2 Impulse response to news shocks and variable capacity utilization

We first study the impulse responses of output, sales and inventories to 4-period positive news shocks to productivity and labor wedge. That is, at period 0, agents get signals that future productivity ( $\mathbb{E}_0 z_4$ ) will increase or future labor wedge ( $\mathbb{E}_0 \psi_4$ ) will decrease.<sup>11</sup>

Figure 2 reports the impulse responses. Note first that consumption and investment, which are the two components of private sales, increase immediately, and during all subsequent periods. Consumption increases because of the wealth effect associated with the good news, and investment increases because of the presence of investment adjustment costs.

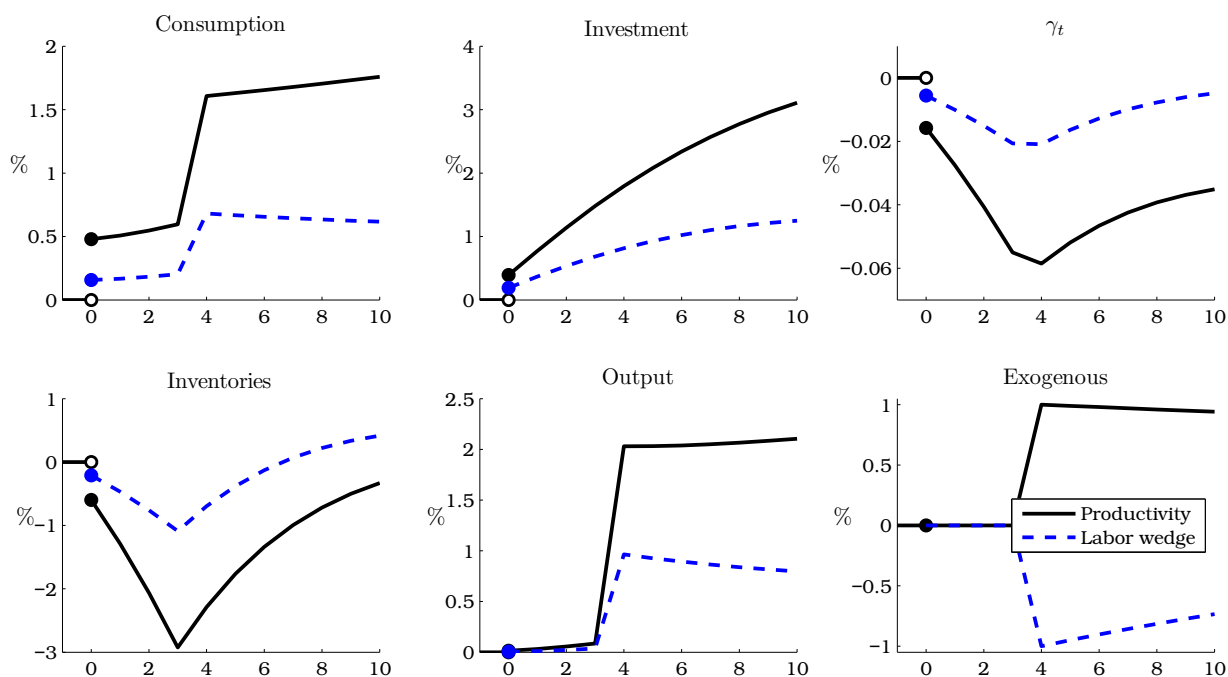


Figure 2: Impulse responses to news shocks in the stock-elastic demand model. Solid line: 4 period news about productivity; dashed line: 4 period news about the labor wedge. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.

In line with our previous discussion, inventories fall. The fall is large and persistent, and reaches its trough in the period preceding the realization of the change in fundamentals. At the same time, output remains mostly unchanged until period 4, when fundamentals change. That is, the increase in sales during the news period is almost entirely met by inventory disinvestment. To build further

<sup>11</sup>We define a positive news shock as a shock that generates an increase in sales. When the labor wedge is expected to decrease, then households expect to face less disutility of working in the future. This will also boost current sales.

intuition for the responses of inventories, note that labor market clearing implies that:

$$\psi_t n_t^{\frac{1}{\xi}} = \alpha m c_t z_t k_t^{1-\alpha} n_t^{\alpha-1}, \quad (28)$$

so that marginal cost is given by:

$$\widehat{m}c_t = \omega \hat{y}_t - \hat{z}_t + \hat{\psi}_t - (\omega + 1)(1 - \alpha)\hat{k}_t. \quad (29)$$

This equation tells us that both news about an increase in future productivity and news about a decrease in future labor wedge would contribute to a decline in future marginal cost. In general equilibrium, this downward pressure in the marginal cost profile is reflected in the negative impulse response of the expected discounted marginal cost  $\gamma_t$ , which we report in the upper right panel of figure 2. Since inventories are used to smooth out the difference in marginal cost of production over time, this fall in the expected discounted marginal cost leads to a fall in inventories which is sufficient to overcome the effect of the increase in sales, as indicated by equation (22).

Note that we are not forcing output to be fixed during the news period and that there still is a small increase in output for the first four periods. Although capital is fixed in the short run, and both productivity and the labor wedge are unchanged during the news period, the labor demand schedule of firms may still shift with changes in marginal cost, as we see from the right hand side of equation (28). Indeed, in contrast to models without inventories, the optimal pricing policy of firms does not imply that marginal cost is fixed — instead, it is the expected discounted marginal cost that is constant. Through equation (28), the increase in demand is associated to a rise in marginal cost which shifts out the labor demand curve, resulting in a small increase in hours worked. However, since the marginal cost is effectively smoothed out by the strong inventory substitution channel in our economy, the actual movement in marginal cost is small and therefore labor only slightly increases in equilibrium. Therefore the small change in output is an optimal response of the economy with inventories.

To make this point more clear, we allow capacity utilization to vary. Denoting  $u_t$  as the utilization of capital at period  $t$ , the production function and the capital accumulation function are

modified as follows:

$$y_t = z_t(u_t k_t)^{1-\alpha} n_t^\alpha,$$

$$k_{t+1} = (1 - \delta(u_t))k_t + \left[1 - \phi\left(\frac{i_t}{i_{t-1}}\right)\right] i_t,$$

where  $\delta(1) = \delta_k$ ,  $\delta'(\cdot) > 0$  and  $\delta''(\cdot) > 0$ . In words, higher utilization of capital increases output, but this comes at a cost of higher rate of depreciation of capital. In a model without inventories, such as [Jaimovich and Rebelo \(2009\)](#), capacity utilization increases with news about a future rise in productivity. This is because with a future rise in productivity, the presence of investment adjustment costs leads to an increase in capital investment today. The increase in capital investment generates a fall in the value of installed capital. At the same time, the positive income effect from the household generates a fall in the marginal value of income due to the concavity of the utility function. Overall, the fall in the value of installed capital is steeper than the fall in the marginal value of income, and therefore capacity is utilized more to satisfy the additional demand.

In [figure 3](#), we plot the impulse responses for the inventory model with variable capacity utilization. As we see, the quantitative response of capacity utilization during the news period is modest. Utilization significantly increases only after the shock realizes.

The small response of capacity utilization during the news period comes directly from the household preference and the role of inventories in the economy. The marginal value of income  $\lambda$  in our model with GHH preference is the following:

$$\lambda = \left(c - \psi \frac{n^{1+\xi^{-1}}}{1 + \xi^{-1}}\right)^{-\sigma}.$$

In this economy, the increase in consumption and investment can be matched by depleting inventories, rather than working more or utilizing capital more intensively. As in the baseline model, hours do not need to rise along with the increase in consumption. The response of hours generates a steeper fall in the marginal value of income than in a model without inventories. In turn, the steeper fall in the marginal value of income means that Tobin's Q falls by less, in relative terms. This implies that increased capacity utilization (which uses up installed capital) is a less attractive way of meeting the increase in sales. Instead, firms prefer to sell out of stock in order to meet

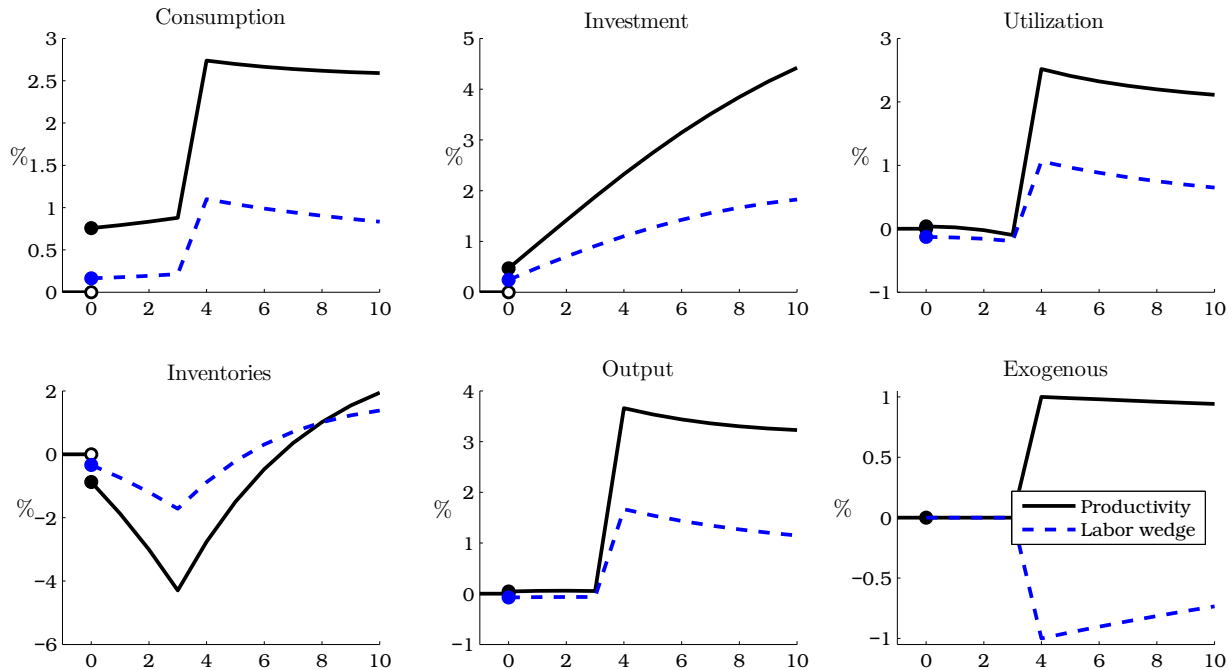


Figure 3: Impulse responses to news shocks in the stock-elastic demand model with variable capacity utilization. Utilization parameter:  $\delta_k''(1) = 0.34$ ; solid line: 4 period news about productivity; dashed line: 4 period news about the labor wedge. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.

the increase in demand. Thus, the negative comovement between inventories and sales in response to news shocks is an equilibrium outcome, even when we allow for production to increase in the short-run, either through increased utilization of labor or of capital.

### 4.3 Do surprise shocks generate positive comovement?

While news shocks generate a persistent negative comovement between inventories and sales, one may wonder whether this also occurs after surprise innovations to fundamentals. The impulse responses reported in figure 4 show that this is not the case. Inventories, consumption, investment and output all increase in response to surprise innovations to productivity and the labor wedge. The short-run response of the inventory-sales ratio is also consistent with its observed countercyclicality at business-cycle frequencies, in line with the findings of [Khan and Thomas \(2007a\)](#) and [Wen \(2011\)](#).<sup>12</sup> For this type of shock, the model's predictions are thus broadly consistent with the

<sup>12</sup>The countercyclicality of the inventory-sales ratio is not completely robust to the calibration of the shock, as it depends partly on the magnitude of the initial increase in sales. For a smaller persistence of productivity shocks of  $\rho_z = 0.8$ , for example, the response of sales is more muted, and the IS ratio becomes procyclical. This behavior of the

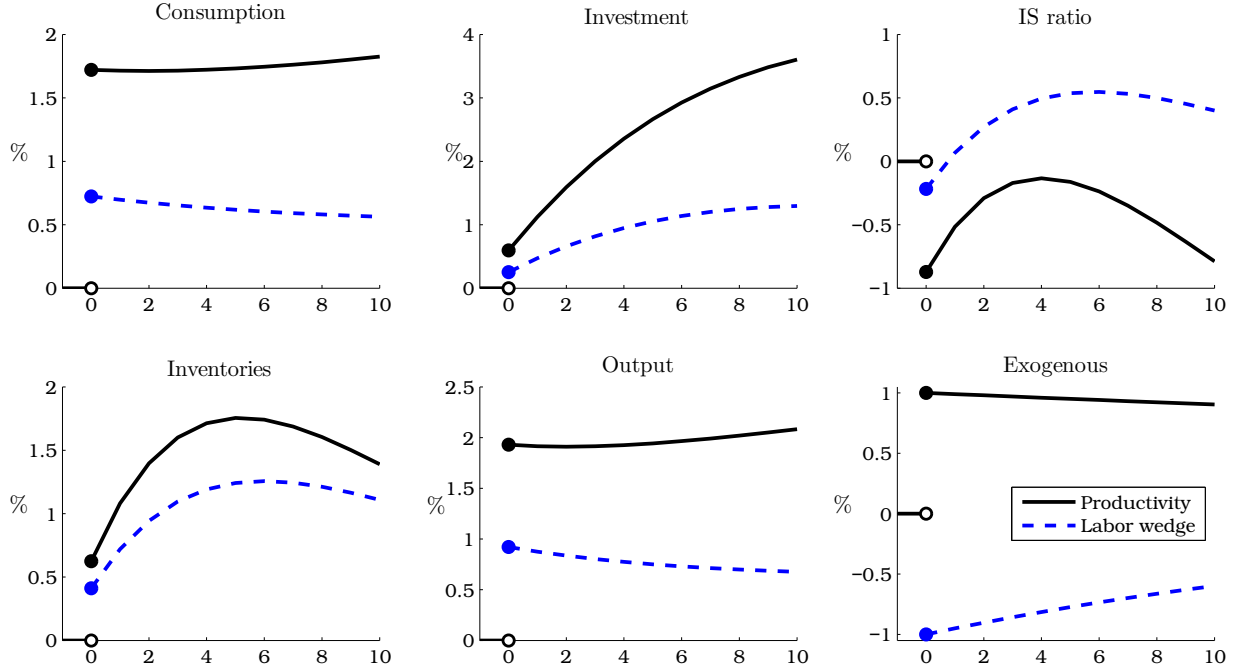


Figure 4: Impulse responses to surprise shocks in the stock-elastic demand model. Solid line: productivity; dashed line: labor wedge. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.

observed behavior of inventories and sales over the business cycle. Thus, the negative comovement of inventories and sales is an identifying feature of news shocks relative to non-news shocks.

#### 4.4 Other types of news shocks

Although the two types of shocks we have considered up to now have been found to be significant sources of news in the literature (Schmitt-Grohé and Uribe, 2012), we do not need to limit our result to these shocks. In fact, proposition 2 implies that the negative comovement holds for any type of news shocks, since on impact, all news shocks share the feature that no fundamentals change.

In this section, we consider two other types of news shocks: discount factor shocks and government spending shocks. First, consider a news shock to the discount factor. When the discount factor is expected to increase in the future, then households expect that in the future they will consume more and save less. They will then consume less today since they now discount the future

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inventory-sales ratio has motivated Kryvtsov and Midrigan (2013) to investigate the ability of countercyclical markup movements to mute inventory increases in response to demand-side shocks, since in the data, the inventory-sales ratio is countercyclical. However, in response to both productivity and demand shocks, the procyclicality of inventories holds regardless of the values of the persistence parameters  $\rho_z$  and  $\rho_\psi$ .

less. Moreover since savings and hence investment will decrease in the future, with investment adjustment costs, investment will also start decreasing today. Therefore, news about an increase in future discount factor generates a fall in sales. At the same time, the fall in investment leads to an decrease in future capital, which generates an increase in the future marginal cost. Therefore, inventories will increase, confirming that the negative comovement property holds with this type of news shock.

Second, when there is a future increase in government spending, then inventories will increase to build up for the demand from government spending, since marginal cost is expected to rise in the future with the additional demand from the government. At the same time, since the households in the end take the burden of this spending, consumption and investment falls. Again, there is negative comovement between inventories and sales with this type of news shock as well.

Figure 5 shows the impulse responses to these two shocks.<sup>13</sup> As discussed, the negative comovement property also holds, and even after impact.

## 4.5 Adding adjustment costs

Adding adjustment costs to capital investment is a crucial ingredient to generate an investment boom in response to news shocks (Jaimovich and Rebelo, 2009). Capital is slow to adjust, and with this form of adjustment cost, investment decisions depend on the whole expected future path of the marginal value of capital, or future Tobin's Q. News shocks affect the marginal productivity of future capital, and thus raise future Tobin's Q, which directly translates into an increase in current investment.

The rationale for imposing adjustment on inventory investment is less clear, in particular in the case of finished-good inventories. First, whereas building a factory or machinery takes time and hence requires adjustment periods, stocking or depleting an already existing product should be the most flexible adjustment that firms can take. Second, as we discussed in the previous sections, it is not the level, but the growth rate of marginal cost that is important for finished-good inventory investment decisions. Therefore, adding adjustment costs to finished-good inventory investment is a less appealing approach.

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<sup>13</sup>The persistence of each process is 0.17 for the discount factor, and 0.95 for government spending. These values are those estimated by Schmitt-Grohé and Uribe (2012).

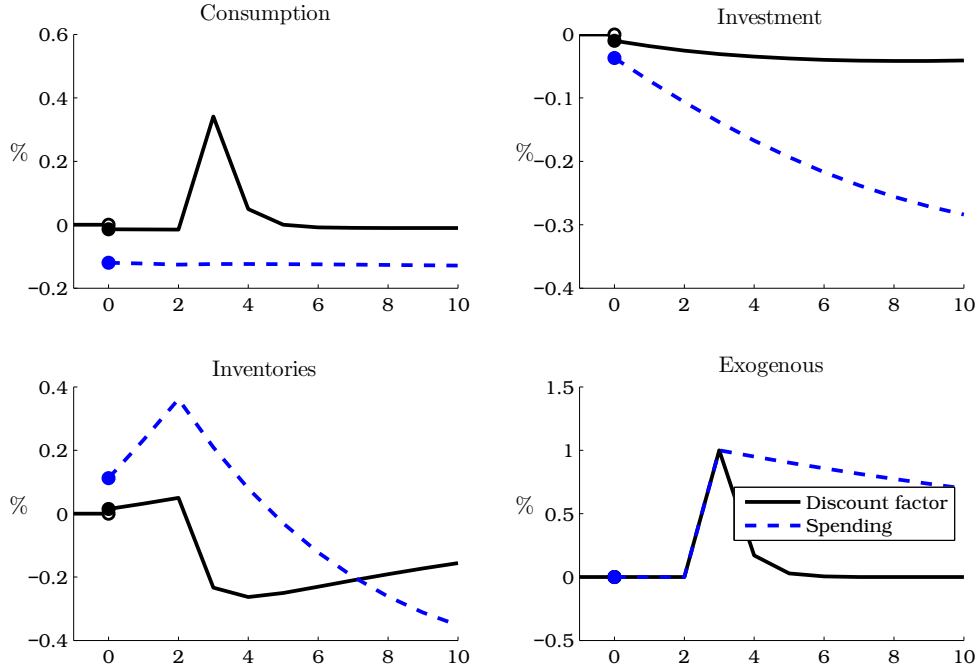


Figure 5: Impulse responses to other news shocks in the stock-elastic demand model. Solid line: 4 period news about the discount factor; dashed line: 4 period news about government spending. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.

However, adjustment costs to the stock of inventories may have a better justification: the total stock of inventories do seem large and slowly moving. Moreover, our intuition tells us that with a positive news shock, we need additional channels for production to increase and adjustment costs may be helpful in that respect. We consider three possible types of adjustment costs: adjustment costs to inventories, output and on-shelf goods. Adjustment costs to inventories penalize immediate inventory depletion and thus weaken the intertemporal substitution motive. Adjustment costs to output force firms to smooth out the response of output to the shock, and in turn reduce the incentive to deplete inventories to satisfy sales. Finally, adjustment costs to goods on shelf affect the sum of output and past inventories. Making adjustment costs bear on this variable might have effects that combine both types of adjustment costs described above.

These adjustment costs are introduced by assuming that the law of motion for inventories is



modified as follows:

$$inv_t = (1 - \delta_i)inv_{t-1} + y_t - s_t - ADJ_t,$$

where  $ADJ_t$  is the adjustment cost of each type. We assume the following form:

$$ADJ_t = \phi_x \left( \frac{x_t}{x_{t-1}} \right) x_t, \quad x \in \{inv, y, a\},$$

where  $\phi_x(1) = \phi'_x(1) = 0$  and  $\phi''_x(1) > 0$ . In figure 6, we show the responses of the model with and without adjustment costs. We experiment with different levels of adjustment costs, and for all values, we observe that the initial fall in inventories are smaller in both models with adjustment costs, but not close to being positive. We conclude that adjustment costs to inventories and output are not sufficient to generate a procyclical response of inventories.

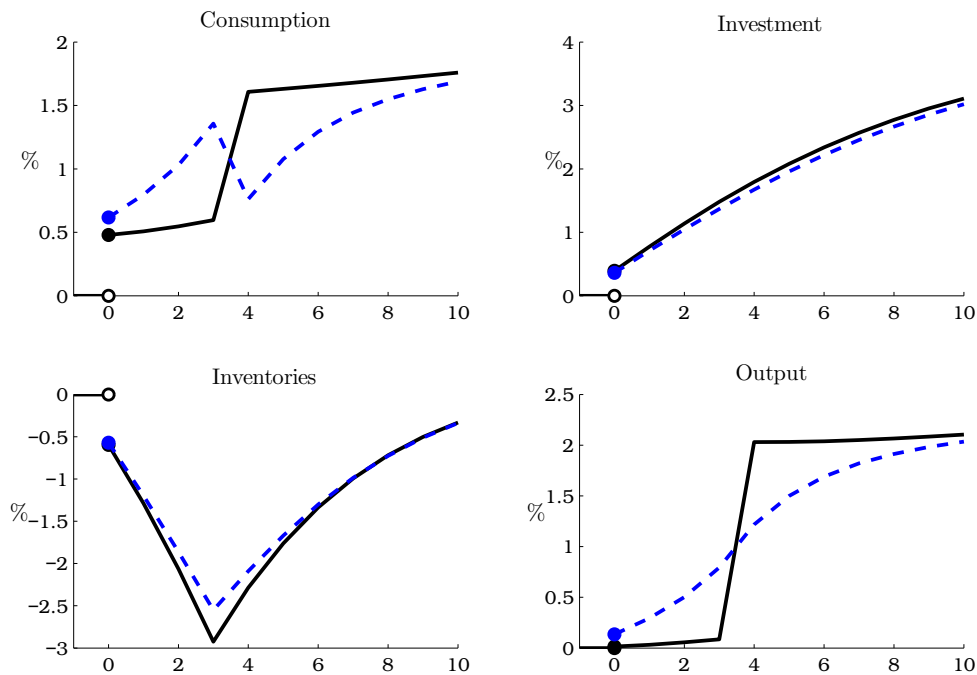


Figure 6: Robustness of impulse responses to output adjustment cost. Impulse responses to 4 period productivity news shock. Solid line: without output adjustment cost; dashed line: with output adjustment cost. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.

The logic behind this result is that with adjustment costs to inventories or production, firms are

now more willing to smoothly adjust their stock of inventories, and hence produce more today when there is good news. However, to make this happen, wages must increase to induce households to work more. With an increase in wages, households have more income, and consumers will increase their current consumption level. This additional increase in consumption, arising from an increase in wages, partially offsets the effect of the increase in output on total inventory accumulation.

## 5 Robustness: Other inventory models

A natural question is whether our result is specific to the particular inventory model we have chosen to analyze. In this section, we discuss models with alternative micro-foundations for inventory holdings. Leading business-cycle models introduce inventories either as buffers against uncertainties in demand at the firm level (stockout-avoidance models), or as stocks associated with nonconvex delivery costs at the firm level (Ss inventory models). We will focus more on the first approach since it provides a better account of finished-good inventory behavior (Khan and Thomas, 2007a). Nevertheless, we also discuss the second approach for completeness.

A summary of the discussion is that our result holds for all other models as well. This is because one important role for inventories in all of these models is the intertemporal substitution channel. With inventories, producers are allowed to flexibly change their production schedule based on their perception of the intertemporal cost profile. Since news shocks directly affect this perception, the other margins which differ across models matter less.

### 5.1 Stockout-avoidance model

One branch of the literature on finished-good inventories motivates inventories by introducing a lag between production and the realization of sales. These "stockout-avoidance models" additionally assume that firms have imperfect information on their idiosyncratic demand schedule at the time they make production decisions. When realized demand for their product is unusually high, firms may run out of available product — a "stockout" — and lose potential sales. This motivates firms to put, on average, more on-shelf goods than they expect to sell, and carry over excess goods as inventory into the next period.<sup>14</sup>

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<sup>14</sup>This mechanism is consistent with existing evidence that stockouts occur relatively frequently at the firm level. Bils (2004) uses data from the BLS survey underlying the CPI and estimates that stockout probabilities in this

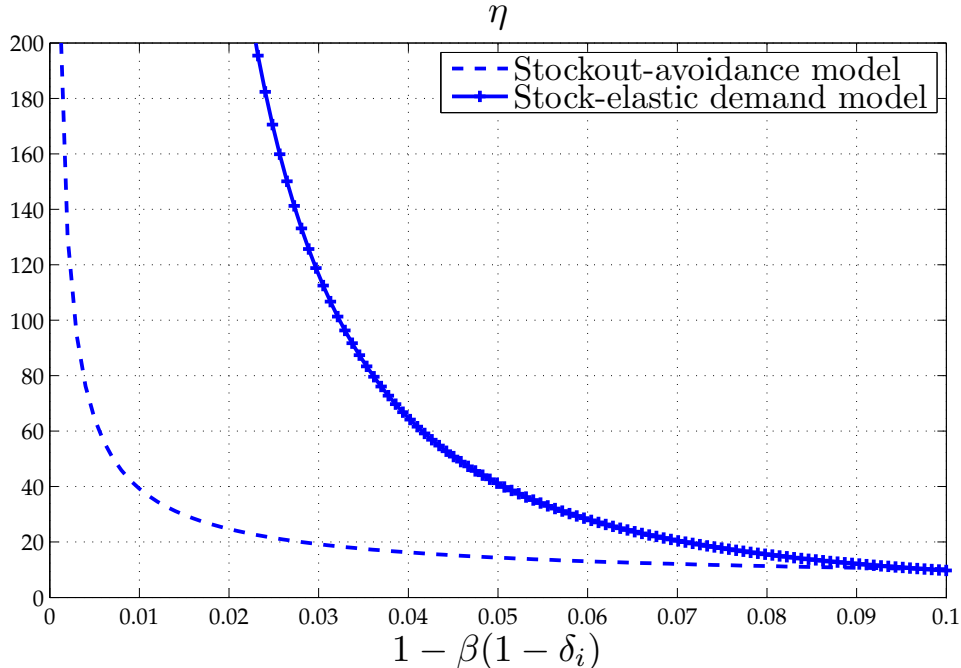


Figure 7: Value of  $\eta$  as a function of  $1 - \beta(1 - \delta_i)$ , in the stockout-avoidance model, holding fixed all the other structural parameters. For comparison,  $\eta$  for the stock-elastic demand model, same as figure 1, is also plotted.

In an online appendix, we study the effects of news shocks in this class of models in detail. We show that a reduced-form framework similar to that of proposition 1 obtains, and moreover that our main result carries through: in response to good news about the future, under standard calibrations of the model, sales increase while inventories fall<sup>15</sup>. Additionally, we argue that, as in the stock-elastic demand model, the main mechanism dominating the response of inventories to news shocks is intertemporal substitution in production. In figure 7, we plot the value of  $\eta$ , the degree of intertemporal substitution, as a function of the intertemporal cost. Again, we see that even with large intertemporal substitution costs, the degree of intertemporal substitution is strong.

The similarity of the two classes of models comes from the fact that the optimal stocking condition (18) also holds in the stockout-avoidance model. The cost of stocking is the marginal cost. The benefits of stocking are twofold: (i) in case sales turn out to be higher than expected,

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dataset are roughly 5 percent. More recently, using supermarket-level data for a large retailer, Matsu (2011) suggests that stockout probabilities are in the range of 5 – 10 percent. See Kahn (1987, 1992), Kryvtsov and Midrigan (2010, 2013), and Wen (2011) for detailed analysis of the properties of this class of models.

<sup>15</sup>This follows from obtaining analytical restrictions on reduced-form parameters to precisely quantify the conditions under which this result holds.

the firm can increase its sales by stocking more output; (ii) in case sales turn out to be lower than expected, the firm can lower future production costs by stocking output as inventories. It turns out that even in this class of models, the intertemporal substitution motive is quantitatively stronger for news shocks.

## 5.2 (S,s) inventory model

The existence of nonconvex delivery costs at the firm level has also been claimed to be a potentially important motive for holding inventories, albeit mainly input inventories, as opposed to finished-good inventories on which our analysis has so far focused. In the model of [Khan and Thomas \(2007b\)](#), the firm pays a fixed cost when placing an order for inputs. This cost comes is i.i.d. across firms and over time, and generates a steady-state distribution of firms with different levels of inventories. In this model, the optimal stocking condition for stock-adjusting firms also balances the cost and benefit of ordering goods, along the lines of the discussion of equation (18). To be precise, the cost of stocking is the total cost of goods and a fixed delivery cost. The benefits of stocking are twofold: (i) in case sales turn out to be higher than expected, firms will not order at that time. The total production capacity of the firm is then constrained by the amount of input inventories it holds. Hence, more input inventories allow the firm to produce more goods when demand is high but delivery cost becomes too high. (ii) In case sales turn out to be lower than expected, firms can order at that time as well. In this case, the firm will reduce its total cost if it expects that the unit cost of goods will be high in the future.

In response to news about an increase in future productivity, firms understand that future demand will increase. At the same time, they understand that future unit costs of input inventories are also cheaper. We solved for the perfect foresight transition dynamics with a news shock to productivity in [Khan and Thomas \(2007b\)](#).<sup>16</sup> Along this path, as in the case of the other models, inventories fall in the short-run, while sales increase.

Overall, these alternative models also have the feature that, in response to good news about the future, inventories fall while sales increase, especially right before the realization of the shock. Therefore, we conclude that the strong intertemporal substitution channel with news shocks is a common feature of all inventories models.

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<sup>16</sup>Refer to [Khan and Thomas \(2007b\)](#) for the solution algorithm.

## 6 Estimating the importance of news shocks I: SVAR approach

Our analysis of inventory models suggests that the negative comovement of inventories and sales is a defining feature of news shocks. In this section, we use this structural restriction to estimate the importance of news shocks.

The approach we take in this section is to estimate a structural VAR with sign restrictions. Since the robust prediction of our theoretical analysis is that news shocks generate negative comovement between inventories and sales, we will use this prediction directly to estimate the explanatory power of news shocks. The appealing aspect of our sign restriction VAR approach is that we can remain agnostic as to other identifying features, and therefore robustly identify shocks without misspecification concerns. On the other hand, a drawback of this approach is that identification of shocks is weaker, in the sense that we may be capturing non-news shocks that could also drive negative comovement between inventories and sales.

### 6.1 Data

We use four observables in our exercise: inventories, consumption, investment and output. Consumption includes nondurables and services, investment includes fixed investment and durables, and output is GDP. For inventories, we used nonfarm private inventories as a whole, or only retail trade inventories to focus on finished-good inventories. However, our results are not sensitive to the type of inventories used for estimation. Therefore, in this section, we present results for nonfarm private inventories. All data are seasonally adjusted, and expressed in real per capita terms. Our sample period is 1955Q1–2006Q4.<sup>17</sup>

### 6.2 Baseline specification and estimation

Our baseline identification strategy imposes that on impact, there is disinvestment in inventories, whereas consumption and fixed investment increase.<sup>18</sup> The VAR model we estimate is the following:

$$X_t = A + B(L)X_{t-1} + U_t.$$

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<sup>17</sup>The sources of the data are NIPA tables 1.1.5 and 5.7.6.

<sup>18</sup>On impact, a fall in inventories is equivalent to a fall in inventory investment, since the impulse response is from the steady state. The joint restriction on consumption and investment is not restrictive since in the data, the two series are highly correlated.

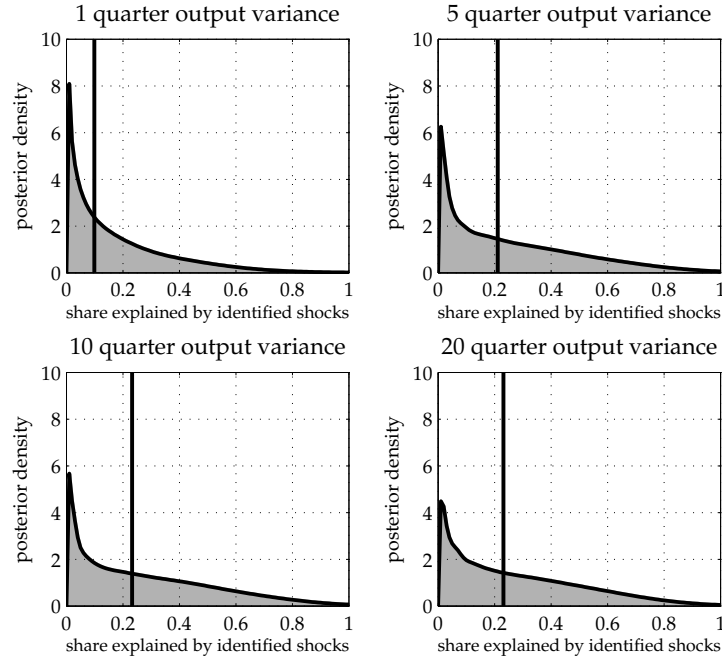


Figure 8: Output variation accounted for by shock identified using impact restrictions. Posterior probability density and the median (vertical line) for the share of forecast error variance at each horizon.

For  $X_t$ , we use log levels of each variable, in order for the estimation to be robust to the presence of cointegrating relations. We estimate the model with a constant term and four lags.<sup>19</sup> We use Bayesian methods, with a diffuse prior for both the coefficients of the autoregressive structure and the variance-covariance matrix of the error terms. Each draw from the posterior identifies a set of possible impulse responses satisfying our impact restriction, and we use a uniform conditional prior on the identified set to draw from the posterior of the impulse responses, following Moon, Schorfheide, and Granziera (2013). Using 20000 draws, the posterior distribution of the forecast error variance (FEV) of output accounted for by these identified shocks is computed.<sup>20</sup>

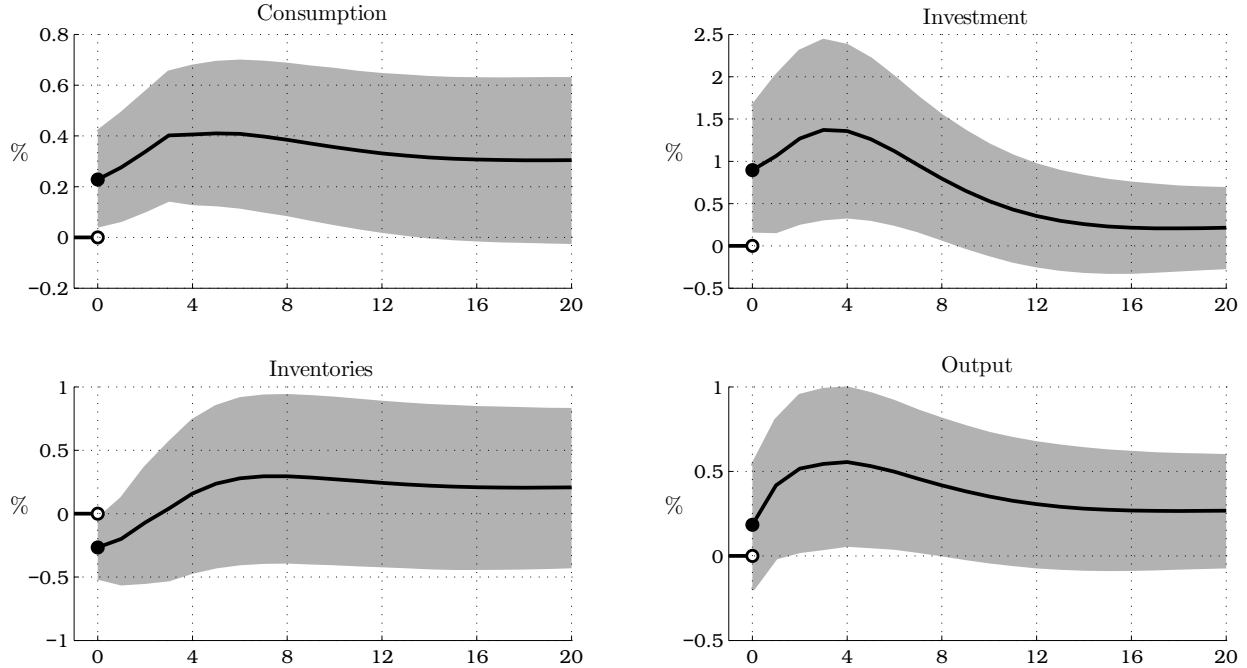


Figure 9: Impulse responses to shock identified using impact restrictions. Median (solid line) and 80% credible set.

### 6.3 Baseline result

Figure 8 reports the posterior distribution of the FEV of our identified shocks on output, for different horizons.<sup>21</sup> The posterior has a sharp mode close to zero, and the median is close to 20 percent at most horizons. In figure 9, we plot the set of identified impulse responses. The median response to our identified shock generates a persistent boom in consumption and investment, and a moderate boom in output. The fall in inventories is short lived; on average, inventory investment occurs immediately after the initial disinvestment, and the stock of inventories becomes positive after 3 quarters. Note that in our model, this is also the case when good news are expected to materialize in the near future. Therefore, our identified shock resembles short-horizon news, with news lasting for only 1 period.

Our identification strategy only imposes impact restrictions, and therefore we are not able to distinguish between short and long-horizon news shocks. Since the focus of the news literature

<sup>19</sup>The Schwartz information criterion suggests two lags. The results to follow are not sensitive to the number of lags.

<sup>20</sup>Our result to follow is not sensitive to adding more draws.

<sup>21</sup>As noted above, we plot the case for nonfarm private inventories but the plot is similar with retail trade inventories as well.

Parameter	Distribution	Median	95%	5%
$\delta_i$	Beta	0.01	0.05	0.00
$\tau(\zeta)$	Gamma	0.7	3	0.05
$\phi_y$	Gamma	3	6	0.60

Table 2: Distribution for the inventory parameters. The parameter  $\tau$  is the steady-state inventory-sales ratio.

is not on one or two quarter news shocks, but rather longer horizons, our next step is to impose restrictions beyond impact.

#### 6.4 Extension: Dynamic restriction

An immediate extension from our identification strategy is imposing that inventory investment falls for two periods whereas consumption and investment increase for two periods. In doing so, we claim that short-horizon news shocks are excluded from our identification and hence we will be able to focus on long-horizon news shocks.

To verify this claim, we test our identification strategy on simulated data from an estimated medium-scale DSGE model.<sup>22</sup> In particular, we add inventories to the model estimated in [Schmitt-Grohé and Uribe \(2012\)](#), and simulate the impulse responses for different horizons of news shocks<sup>23</sup>. For each horizon of the news shocks, we test whether our identification strategy is satisfied or not. We take a probabilistic approach since the newly introduced parameters related to inventories are not estimated by [Schmitt-Grohé and Uribe \(2012\)](#).

In table 2, we specify the distribution of the three new parameters. These are  $\delta_i$ , the depreciation rate of inventories,  $\zeta$ , the elasticity of sales to stock of goods, and  $\phi_y$ , the output adjustment cost. For  $\zeta$ , specifying a distribution directly on this parameter is difficult since the value has a theoretical lower bound at

$$\underline{\zeta} = \frac{1 - \beta(1 - \delta_i)}{\beta(1 - \delta_i)}(\theta - 1),$$

so that the lower bound changes with different draws of  $\delta_i$ . Rather than directly forming a distribution on  $\zeta$ , we specify a distribution of the transformed parameter  $\tau = (\zeta - \underline{\zeta})/\underline{\zeta}$ , which is the steady-state inventory-sales ratio.

<sup>22</sup>This part may be skipped if the reader finds the claim to be straightforward.

<sup>23</sup>The model used for this simulation is described in detail in Appendix.



2 period restriction	4Q news	2Q news	surprise
productivity	1	1	0
labor wedge	1	1	0
discount factor	1	1	0
spending	1	1	0
3 period restriction	4Q news	2Q news	surprise
productivity	1	0	0
labor wedge	1	0	0
discount factor	1	0	0
spending	1	0	0

Table 3: Success probability of identifying assumption.

In table 3, we show the success probability of our identification approach with different horizons of news shocks.<sup>24</sup> For the shocks we consider, our dynamic restriction is successful in identifying longer horizon news shocks.

## 6.5 Estimation result and discussion

Figure 10 reports the posterior distribution of the FEV of output attributable to our identified shocks, when the following restriction is used to identify them: inventory disinvestment occurs for 2 periods, and at the same time both consumption and investment increase for 2 periods. We see that the posterior has a sharp mode close to zero, and the median is now close to 10 percent at all horizons, about half smaller than the result with impact restrictions only. To get a sense of the information that inventories deliver, figure 10 also plots the posterior distribution of the FEV when only consumption and investment are above the steady state for 2 periods. As we see, without the inventory restriction, the distribution is disperse and the median share of FEV for the set of shocks that drive positive comovement of consumption and investment is 30 percent overall. Hence with inventories, the posterior density becomes much tighter, and the median share of the shock falls by about 67 percent.

Figure 11 reports the impulse responses to the identified shock with 2 period restrictions. Inventory disinvestment occurs for 2 periods, but after that, there is again investment in inventories. Consumption and investment increase, but the increase in output is now modest.

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<sup>24</sup>We focus on the stationary shocks in [Schmitt-Grohé and Uribe \(2012\)](#). We exclude investment specific shocks since our model has two types of investment (capital and inventories), which makes the meaning of this shock is less clear. For example, one important change in productivity specific to inventory investment is the introduction of just-in-time technology, which should also have an effect on the accumulation of capital goods.

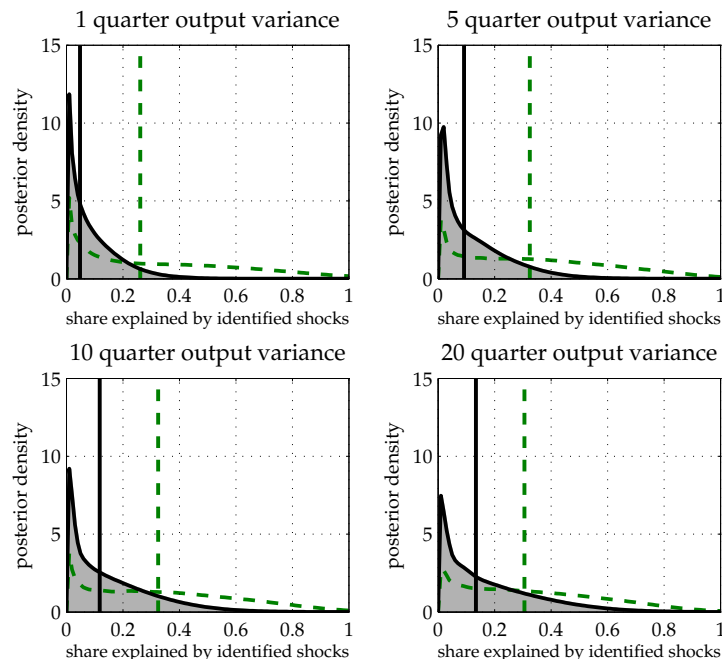


Figure 10: Output variation accounted for by shocks identified using 2 period restrictions. Posterior probability density and the median (vertical line) for the share of forecast error variance at each horizon. Solid line: 2 period negative comovement between  $\Delta inv_t$  and  $(c_t, i_t)$ . Dashed line: 2 period positive comovement between  $c_t$  and  $i_t$ .

We also extend our dynamic restriction to 3 periods, that is 3 periods of inventory disinvestment accompanied by increases in consumption and fixed investment. As in figure 12, the median share of FEV explained by the identified shock is now below 5 percent in most horizons, and tight with basically no probability assigned above 20 percent. Therefore, our news shocks identified with 3 period restrictions *at most* account for 20 percent of output variation. Figure 13 reports the impulse responses of the identified shock with 3 period restrictions. Although the movement in output is modest, it actually declines on impact.

We summarize the key points of our empirical results as follows: (i) the identified impulse response with impact restrictions suggest that most news shocks are short-lived, with an immediate investment in inventories after the impact disinvestment; (ii) the identified news shock based on impact restrictions explain on average 20 percent of output variations at all horizons; (iii) restrictions beyond impact generate a tighter posterior distribution of output variations; (iv) long-horizon news shocks explain on average 5 percent, and at most 20 percent of output variations at all horizons.

The reason why the FEV turns out to be small is that inventories are a procyclical variable. In

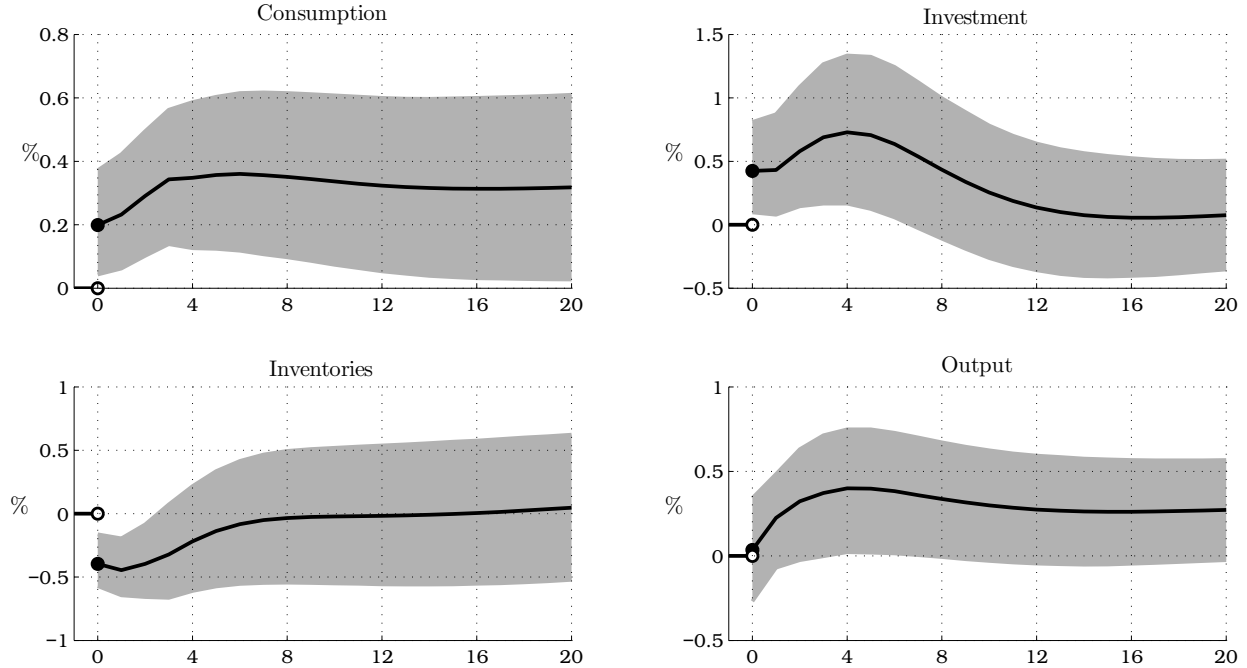


Figure 11: Impulse responses to shocks identified using 2 period restrictions. Median (solid line) and 80% credible set.

the data, the unconditional contemporaneous correlation between inventories and sales (consumption plus investment) is 0.50.<sup>25</sup> Since our identification is based on negative comovement of these generally positively comoving variables, it would come as a surprise if the identified shocks were able to generate the bulk of business cycles.

## 6.6 Robustness

Since our identifying assumption only relates to the sign of the responses of inventories and components of sales, it is robust to changes in specification. We have nevertheless performed several robustness checks. First, we used different priors for the coefficients, such as the Minnesota prior or the Normal-Wishart prior. None of these priors alter significantly the results.<sup>26</sup> Second, when imposing our dynamic restriction, we also tried to be less restrictive by not imposing the negative comovement on impact or second period, in order to control for any demand effects that

<sup>25</sup>This is based on HP filtered data but the result is not sensitive to filtering methods.

<sup>26</sup>Since our focus is mainly on FEV decomposition, it might be more desirable to set a uniform prior on this moment. However, forecast error variance is a highly nonlinear transformation of the VAR coefficients, and existing methodologies do not allow us to easily address this “inverse” problem. As a way to overcome this issue, we are showing our result with and without the negative comovement assumption in order to control for the role of the prior.

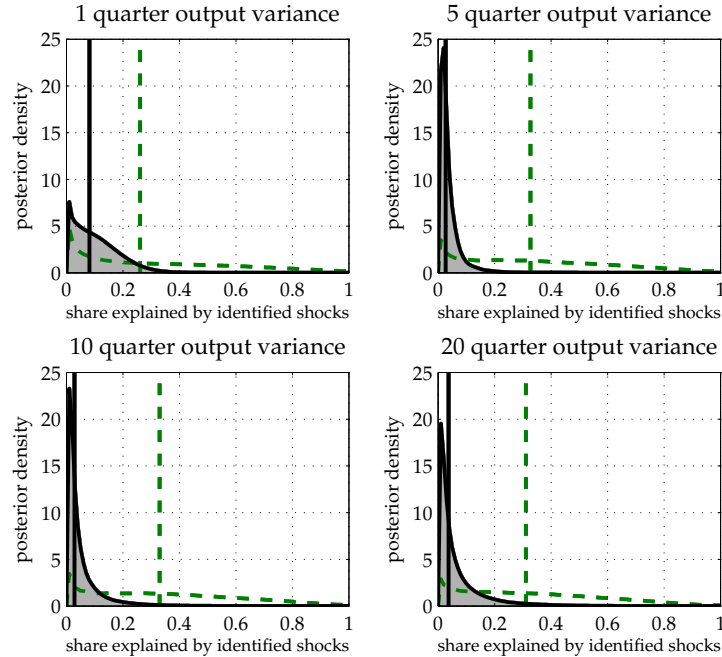


Figure 12: Output variation accounted for shocks identified using 3 period restrictions. Posterior probability density and the median (vertical line) for the share of forecast error variance at each horizon. Solid line: 3 period negative comovement between  $\Delta inv_t$  and  $(c_t, i_t)$ . Dashed line: 3 period positive comovement between  $c_t$  and  $i_t$ .

may remain in the short run with long-horizon news shocks. The result is not sensitive to this change since the stock of inventories move in a persistent manner. For example, by imposing that inventories are below average only in the third period, it mostly follows that inventories are below average for the first and second period as well. Third, as we mentioned above, our result is not sensitive to using different types of inventory data. Fourth, as studied in detail by [McCarthy and Zakrajšek \(2007\)](#), inventory dynamics have changed since the 1980s: while the procyclicality of inventories remains, the volatility of total inventory investment has fallen, possibly because of improvements in inventory management, contributing to the fall in output volatility. To address this issue, we take into account the possibility of different “inventory regimes” in the data by creating two separate samples, before and after 1984, and conduct our empirical exercise on each of the sub-samples. Our results are not sensitive to these various sample splits. This suggests that the nature of the comovement between inventories and private sales did not change substantially around this period.

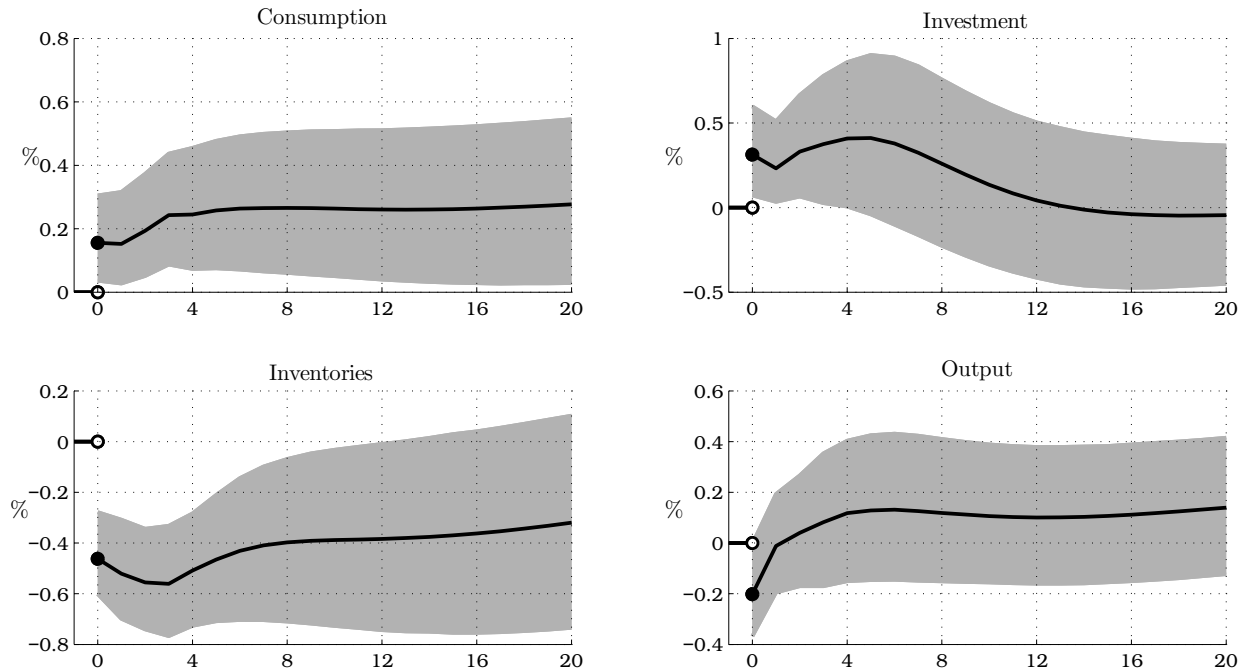


Figure 13: Impulse responses to shocks identified using 3 period restrictions. Median (solid line) and 80% credible set.

## 6.7 Other VAR approaches

Existing methods of identifying news shocks in a VAR setup have typically used data on productivity (Barsky and Sims, 2011), sometimes combining them with data on stock prices (Beaudry and Portier, 2006; Beaudry and Lucke, 2010). Our new piece of information could also be incorporated into these existing approaches. For example, one standard approach in identifying news shocks is to look at movements in stock prices orthogonal to any changes in current productivity. To include the movements of inventories in this estimation strategy, we ran a 3 variable VAR with utilization-adjusted productivity, the S&P 500 index as stock prices, and inventories. We imposed impact zero restriction on productivity, and traced out the dynamics of inventories following an increase in stock prices. We found that the sign of the impact and short-run responses of inventories are inconclusive.<sup>27</sup> This suggests that existing methods are not fully incorporating the information inventories provide about news shocks.<sup>28</sup> This is linked to the fact that the existing literature provides a wide range of numbers for the contribution of news shocks to output volatility. For instance,

<sup>27</sup>This plot is reported in appendix.

<sup>28</sup>A similar point is made in Arias, Rubio-Ramirez, and Waggoner (2013) with regards to the penalty function approach in Beaudry, Nam, and Wang (2011). Our information could add to this debate as well.

while [Beaudry and Portier \(2006\)](#), [Beaudry and Lucke \(2010\)](#) all find that news shocks contribute to 50–60 percent of output variation, a similar approach by [Barsky and Sims \(2011\)](#) finds that news shocks only contribute to 10 percent of output volatility in the short run (1–4 quarters), and about 40 percent in the long run.<sup>29</sup> Our finding is closer to the latter approach, although we find that news shocks should explain less than 20 percent of output volatility even in the long run.

## 7 Estimating the importance of news shocks II: DSGE approach

In this section, we estimate a structural DSGE model incorporating inventories by Bayesian methods, and use the estimates to assess whether news shocks are important contributors to business cycle fluctuations. The purpose of this section is twofold. First, while the agnostic VAR method is robust to misspecification, it is still a partial identification strategy. Using additional information based on the structure of our economy is in principle helpful in identifying news shocks more precisely. Second, our discussion is so far limited to shocks that are stationary. However, an important component of news shocks may be nonstationary and the importance of these nonstationary components are better understood when we directly model them.

It is however important to keep in mind that estimating a structural DSGE model has its own limitations. Our theoretical analysis did not require us to take a stand on a specific view of the structure of the economy. However, to estimate a DSGE model, we need to select a specific model to estimate, so that the results we obtain are potentially subject to misspecification issues.

### 7.1 Model specification

The model we estimate in this section is an extended version of [Schmitt-Grohé and Uribe \(2012\)](#) with inventories introduced as in [Bils and Kahn \(2000\)](#). The model we estimate is similar to that of section 2, and its details are described in an online appendix. However, there are several differences that are worth mentioning here.

First, we allow for two types of nonstationary shocks in the model: nonstationary productivity and nonstationary investment-specific productivity shocks. By allowing for these shocks, we will be able to separately estimate the importance of stationary versus nonstationary news shocks.

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<sup>29</sup>See [Kurmann and Mertens \(2014\)](#) for a comment on the identification scheme of [Beaudry and Portier \(2006\)](#).

Second, we allow for the price markup to change over time. That is, the demand function in (12) is now written as

$$s_t(j) = \left( \frac{a_t(j)}{a_t} \right)^\zeta \left( \frac{p_t(j)}{P_t} \right)^{-\theta_t} x_t,$$

where  $\theta_t$  are assumed to be AR(1) processes.<sup>30</sup>

Third, on top of the seven observables used in Schmitt-Grohé and Uribe (2012), we also use the inventory series described in the previous section as an additional observable in our estimation procedure.

## 7.2 Estimation results

Table 4 summarizes the variance decomposition of the estimated model. While the prior median parameter values imply that news shocks account for 37 percent of output variation, we find that the median posterior estimate drops to 17 percent. This contrasts the result in a model without inventories where 41 percent of output variation could be accounted for by news shocks (Schmitt-Grohé and Uribe, 2012). Therefore, when firms are allowed to adjust inventories in the model, news shocks now play a smaller role. This small contribution of news shocks also holds for fixed investment and inventory investment. For all these variables, news shocks now account for around 10 percent of total variation. However, for other variables such as consumption, government spending, and hours, we still large role for news shocks, consistently with Schmitt-Grohé and Uribe (2012).

To summarize, structural estimation of a DSGE model including inventories indicates that news shocks account for less than 20 percent of output variation over the business cycle, consistently with the results obtained using the VAR approach.

## 8 Conclusion

In this paper, we studied the response of inventories to news shocks. We derived analytical restrictions on structural parameters under which inventories and sales will positively comove in response to news shocks. We showed that these conditions are violated by standard calibrations of the classes of models we study, resulting in negative comovement between inventories and sales

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<sup>30</sup>For  $\theta_t$ , we transform it into the markup  $\mu_t = \theta_t/(\theta_t - 1)$ , and assume that it follows an AR(1) process.

Innovation	Y	C	I	N	G	INV
Prior News Total	37	47	48	39	49	40
Posterior News Total	17	49	10	38	52	14
Stationary Productivity Shock						
News	1	0	0	1	0	1
Current	16	3	8	10	0	14
Nonstationary Productivity Shock						
News	1	1	0	0	0	0
Current	15	10	6	3	4	7
Stationary Investment-Specific Shock						
News	1	1	5	1	0	2
Current	22	4	63	9	0	8
Nonstationary Investment-Specific Shock						
News	0	0	0	0	0	0
Current	0	0	1	0	0	0
Government Spending Shock						
News	1	0	0	1	51	0
Current	1	0	0	1	44	0
Household Preference Shock						
News	4	41	0	6	0	1
Current	3	28	0	5	0	1
Labor Wedge Shock						
News	8	6	3	27	0	4
Current	7	5	3	28	0	4
Price Markup Shock						
News	1	0	1	0	0	6
Current	18	1	9	7	0	47

Table 4: Variance decomposition from estimated model. All values are rounded and are in percentage terms. Y, C, I, N, G, INV refer to the growth rates of output, consumption, fixed investment, hours worked, government spending and inventories, respectively.

in response to news shocks. Our analysis highlighted the key mechanism behind this result: news shocks generate a strong intertemporal substitution motive in production. Moreover, we showed that this mechanism persists during the “news period”, even after introducing various frictions analyzed by the news literature, such as variable capacity utilization and adjustment costs. Lastly, we used the negative comovement between inventories and sales to identify news shocks in postwar US data. We found that news shocks play a small role in aggregate fluctuations, for two reasons: the identified “news period” is short, on average 1 quarter; and the long-horizon shock contributes less than 20 percent of output variation. The insight behind this result is that inventories are procyclical at business-cycle frequencies.



Our work suggests two future directions for progress. First, one contribution of our analysis was to highlight that a key parameter governing the response of inventories to news shocks is the elasticity of inventories to the discounted growth rate of marginal cost. The approach we have taken in this paper is to compute the elasticity implied by existing models of finished-good inventories. An alternative approach is to obtain empirical estimates of this elasticity, and explore modifications of existing models that may match those estimates. Second, we proposed a new way of identifying news shocks, using aggregate data on inventories and sales. An interesting question is whether our theoretical and empirical results could be modified if we were to take a more disaggregated view of inventories, with different sectors having different inventory intensities (Chang, Hornstein, and Sarte, 2009). Theoretically, news shocks in one particular sector may lead to negative comovement of inventories and sales in that sector, but this need not be so in the aggregate. Empirically, differences in the comovement of sales and inventories across sectors, using industry-level data, could be used to identify these sectoral news shocks. We leave this to future research.

## References

- Arias, J. E., J. F. Rubio-Ramirez, and D. F. Waggoner (2013). Inference Based on SVARs Identified with Sign and Zero Restrictions: Theory and Applications. *Mimeo, Duke University*.
- Barsky, R. B. and E. R. Sims (2011). News Shocks and Business Cycles. *Journal of Monetary Economics* 58(3), 273–289.
- Beaudry, P. and B. Lucke (2010). Letting Different Views about Business Cycles Compete. *NBER Macroeconomics Annual* 24.
- Beaudry, P., D. Nam, and J. Wang (2011). Do Mood Swings Drive Business Cycles and is it Rational? *NBER Working Paper* 17651.
- Beaudry, P. and F. Portier (2006). Stock Prices, News, and Economic Fluctuations. *American Economic Review* 96(4), 1293–1307.
- Beaudry, P. and F. Portier (2013). News Driven Business Cycles: Insights and Challenges. *NBER Working Paper* 19411.

- Bils, M. (2004). Studying Price Markups from Stockout Behavior. *Mimeo, University of Rochester*.
- Bils, M. and J. A. Kahn (2000). What Inventory Behavior Tells Us About Business Cycles. *American Economic Review* 90(3), 458–481.
- Caldara, D. and C. Kamps (2012). The Analytics of SVAR: A Unified Framework to Measure Fiscal Multipliers. *Discussion Paper, Federal Reserve Board*.
- Chang, Y., A. Hornstein, and P.-D. Sarte (2009). On the Employment Effects of Productivity Shocks: The Role of Inventories, Demand Elasticity, and Sticky Prices. *Journal of Monetary Economics* 56(3), 328–343.
- Chari, V. V., P. J. Kehoe, and E. R. McGrattan (2000). Sticky Price Models of the Business Cycle: Can the Contract Multiplier Solve the Persistence Problem? *Econometrica* 68(5), 1151–1180.
- Christiano, L. J., C. Ilut, R. Motto, and M. Rostagno (2008). Monetary Policy and Stock Market Boom-Bust Cycles. *European Central Bank Working Paper 955*.
- Copeland, A., W. Dunn, and G. Hall (2011). Inventories and the Automobile Market. *RAND Journal of Economics* 42(1), 121–149.
- Dotsey, M. and R. G. King (2006). Pricing, Production, and Persistence. *Journal of the European Economic Association* 4(5), 893–928.
- Faust, J. (1998). The Robustness of Identified VAR Conclusions About Money. *Carnegie–Rochester Conference Series on Public Policy* 49, 207–244.
- Fisher, J. D. M. and A. Hornstein (2000). (S,s) Inventory Policies in General Equilibrium. *Review of Economic Studies* 67, 117–145.
- Greenwood, J., Z. Hercowitz, and G. W. Huffman (1988). Investment, Capacity Utilization, and the Real Business Cycle. *American Economic Review* 78(3), 402–417.
- Jaimovich, N. and S. Rebelo (2009). Can News About the Future Drive the Business Cycle? *American Economic Review* 99(4), 1097–1118.
- Jung, Y. and T. Yun (2006). Monetary Policy Shocks, Inventory Dynamics, and Price-Setting Behavior. *Federal Reserve Bank of San Francisco Working Paper*.

- Kahn, J. A. (1987). Inventories and the Volatility of Production. *American Economic Review* 77(4), 667–679.
- Kahn, J. A. (1992). Why is Production More Volatile Than Sales? Theory and Evidence on the Stockout-Avoidance Motive for Inventory-Holding. *Quarterly Journal of Economics* 107(2), 481–510.
- Kesavan, S., V. Gaur, and A. Raman (2010). Do Inventory and Gross Margin Data Improve Sales Forecasts for U.S. Public Retailers? *Management Science* 56(9), 1519–1533.
- Khan, A. and J. K. Thomas (2007a). Explaining Inventories: A Business Cycle Assessment of the Stockout Avoidance and (S,s) Motives. *Macroeconomic Dynamics* 11(5), 638–664.
- Khan, A. and J. K. Thomas (2007b). Inventories and the Business Cycle: An Equilibrium Analysis of (S,s) Policies. *American Economic Review* 97(4), 1165–1188.
- Khan, H. and J. Tsoukalas (2012). The Quantitative Importance of News Shocks in Estimated DSGE Models. *Journal of Money, Credit and Banking* 44(8), 1535–1561.
- Kryvtsov, O. and V. Midrigan (2010). Inventories and Real Rigidities in New Keynesian Business Cycle Models. *Journal of the Japanese and International Economies* 24(2), 259–281.
- Kryvtsov, O. and V. Midrigan (2013). Inventories, Markups, and Real Rigidities in Menu Cost Models. *Review of Economic Studies* 80(1), 249–276.
- Kurmann, A. and E. Mertens (2014). Stock Prices, News, and Economic Fluctuations: Comment. *American Economic Review* 104(4), 1439–1445.
- Matsa, D. A. (2011). Competition and Product Quality in the Supermarket Industry. *Quarterly Journal of Economics* 126(3), 1539–1591.
- McCarthy, J. and E. Zakrajšek (2007). Inventory Dynamics and Business Cycles: What has Changed? *Journal of Money, Credit and Banking* 39(2-3), 591–613.
- Moon, H., F. Schorfheide, and E. Granziera (2013). Inference for VARs Identified with Sign Restrictions. *Mimeo, University of Pennsylvania*.

- Mountford, A. and H. Uhlig (2008). What are the Effects of Fiscal Policy Shocks? *Journal of Applied Econometrics* 24(6), 960–992.
- Pindyck, R. S. (1994). Inventories and the Short-Run Dynamics of Commodity Prices. *RAND Journal of Economics* 25(1), 141–159.
- Rotemberg, J. and M. Woodford (1997). An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy. *NBER Macroeconomics Annual* 27.
- Schmitt-Grohé, S. and M. Uribe (2012). Whats News in Business Cycles? *Econometrica* 80(6), 2733–2764.
- Stock, J. R. and D. M. Lambert (2001). *Strategic Logistics Management*. McGraw-Hill/Irwin.
- Uhlig, H. (2005). What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure. *Journal of Monetary Economics* 52(2), 381–419.
- Vukotic, M. (2013). A Sectoral Approach to News Shocks. *Mimeo, University of Warwick*.
- Wen, Y. (2011). Input and Output Inventory Dynamics. *American Economic Journal: Macroeconomics* 3(4), 181–212.
- Woodford, M. (2003). *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press.

# A Detailed equilibrium conditions of the stock-elastic demand model

## A.1 List of equilibrium conditions

A market equilibrium of the stock-elastic demand model is characterized by the following set of equations:

$$\left( c_t - \psi_t \frac{n_t^{1+\xi^{-1}}}{1+\xi^{-1}} \right)^{-\sigma} = \lambda_t \quad (30)$$

$$w_t = \psi_t n_t^{\xi^{-1}} \quad (31)$$

$$\xi_t \left( 1 - \phi \left( \frac{i_t}{i_{t-1}} \right) - \left( \frac{i_t}{i_{t-1}} \right) \phi' \left( \frac{i_t}{i_{t-1}} \right) \right) + \beta \mathbb{E}_t \left[ \xi_{t+1} \left( \frac{i_{t+1}}{i_t} \right)^2 \phi' \left( \frac{i_{t+1}}{i_t} \right) \right] = \lambda_t \quad (32)$$

$$i_t \left( 1 - \phi \left( \frac{i_t}{i_{t-1}} \right) \right) + (1 - \delta_k) k_t = k_{t+1} \quad (33)$$

$$\beta \mathbb{E}_t [(1 - \delta_k) \xi_{t+1} + \lambda_{t+1} r_{t+1}] = \xi_t \quad (34)$$

$$c_t + i_t = x_t \quad (35)$$

$$z_t k_t^{1-\alpha} n_t^\alpha = y_t \quad (36)$$

$$m c_t \alpha \frac{y_t}{n_t} = w_t \quad (37)$$

$$m c_t (1 - \alpha) \frac{y_t}{k_t} = r_t \quad (38)$$

$$(1 - \delta_i) inv_{t-1} + y_t = s_t + inv_t \quad (39)$$

$$s_t + inv_t = a_t \quad (40)$$

$$\mathbb{E}_t \left[ \beta \frac{\lambda_{t+1}}{\lambda_t} (1 - \delta_i) \frac{m c_{t+1}}{m c_t} \right] = \gamma_t \quad (41)$$

$$\frac{1}{\mathbb{E}_t [(1 - \delta_i) q_{t,t+1} m c_{t+1}]} = \mu_t \quad (42)$$

$$\zeta \frac{1}{1 + \frac{inv_t}{s_t}} = \frac{\frac{1}{\gamma_t} - 1}{\mu_t - 1} \quad (43)$$

$$\frac{\theta}{\theta - 1} = \mu_t \quad (44)$$

$$s_t = x_t \quad (45)$$

Conditions (30)-(35) characterize the optimum of the household’s problem, conditions (36)-(43) characterize that of the firm, and condition (45) reflects market clearing for goods. Condition (43) characterizes its optimal choice of inventory holdings, while conditions (42) and (44) characterize optimal pricing by monopolistic firms in this environment. Conditions (39) and (40) are the law of motion for inventories, and the definition of goods on shelf, respectively.

## B Robustness of the results of section 6

We first check whether our result are sensitive to the long-run properties of the data. As an initial verification, we remove non business-cycle frequencies from the data by applying an HP filter to each series. In figure 14, we observe that the impulse responses are quickly mean reverting. However, impulse response patterns are similar to the main text. Moreover, our result on forecast error variances are also similar to our benchmark since in the very short run, the shock accounts for 10 percent of output variation on average, and 30 percent of that in the long run. Comparing the result with no restrictions on inventories, we see that the short run (1 quarter) output variation becomes significantly more precise with a downward shift in the mean.

Second, in our benchmark estimation, we used real GDP as a measure of output. To be consistent with our model definition of output  $y = c + i + \delta inv$ , we also construct an alternative output series which subtracts government spending and net exports from the GDP series. That is, the alternative output measure is nominal GDP net of government spending and net exports, deflated by the GDP deflator, expressed in per capita terms. Figures 15 and 16 again confirm that our result is not sensitive to this extension. In figure 17, we see that by imposing 2 period restrictions, the mean output variation explained by the identified shock shifts significantly downwards at all horizons.

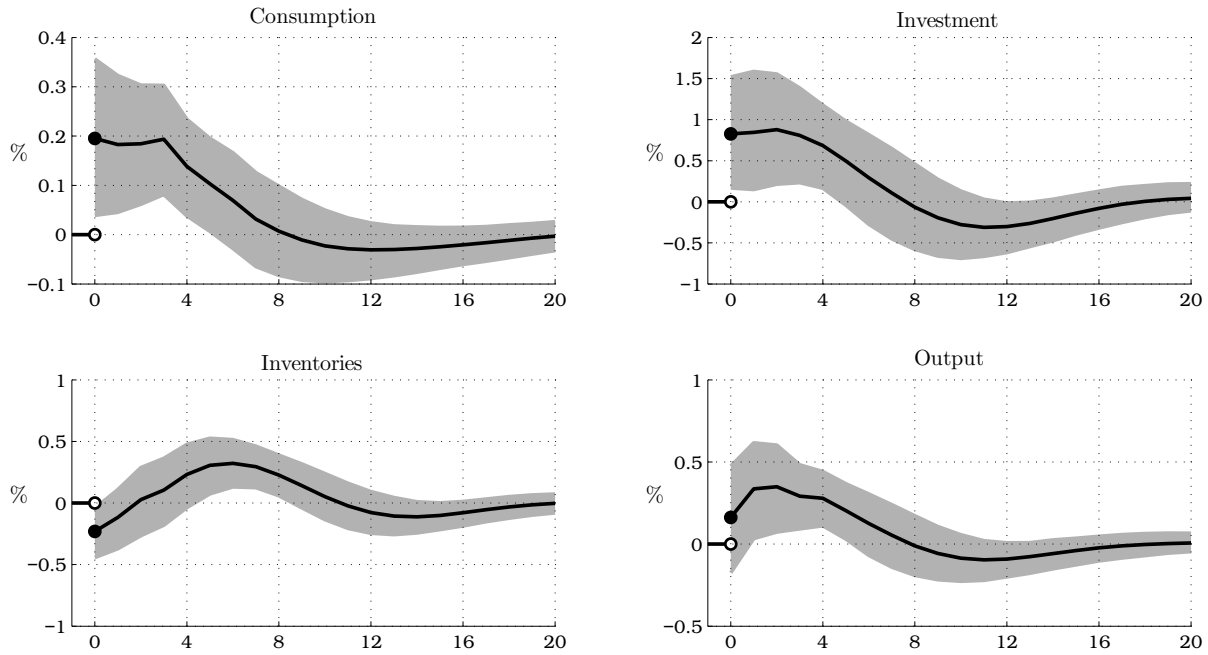


Figure 14: Robustness of impulse responses 1. Median and 80% credible set impulse responses to the shock identified using impact (1 period) restrictions for the HP filtered series.

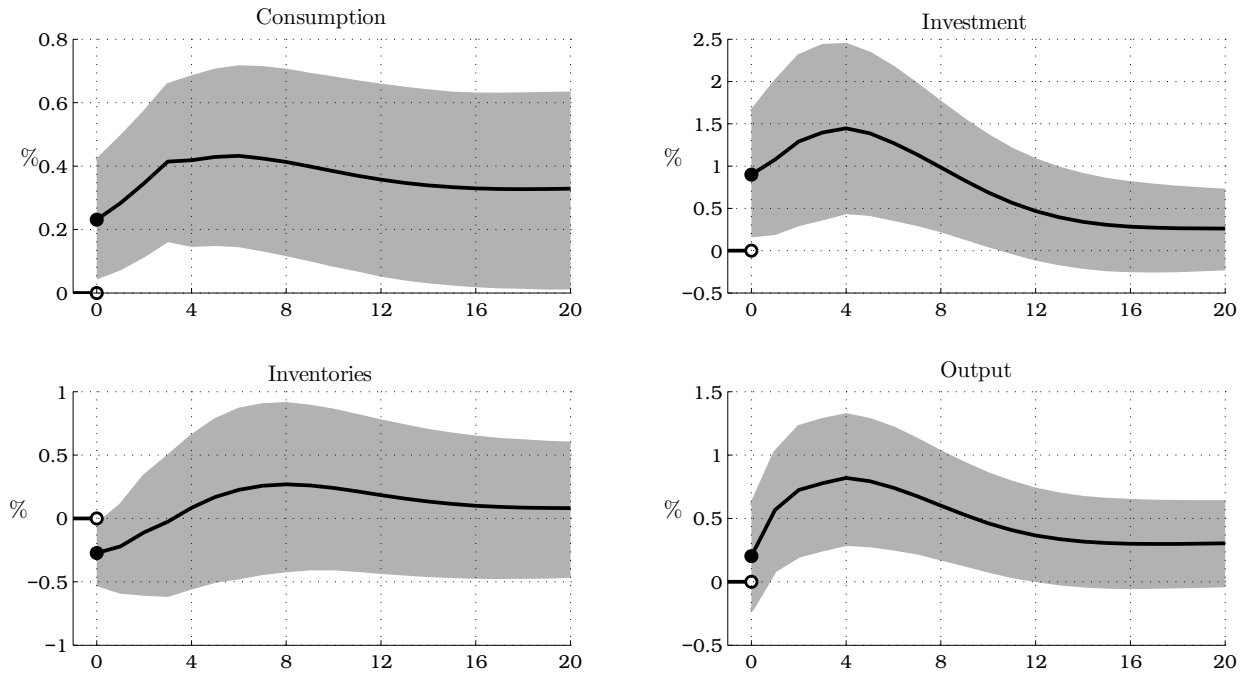


Figure 15: Robustness of impulse responses 2. Median and 80% credible set impulse responses to the shock identified using 1 period restrictions for the alternative output series (without government spending and net exports), with 1 period restrictions applied on inventories, consumption and investment.

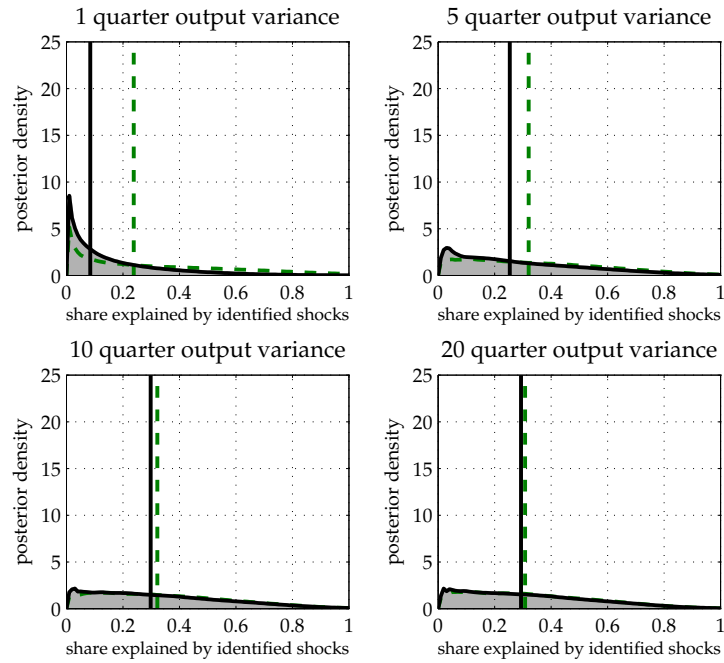


Figure 16: Robustness of forecast error variance 2. Posterior probability density and median (vertical line) for the share of forecast error variance of output at each horizon explained by shocks identified using the alternative output series (without government spending and net exports), with 1 period restrictions. Solid line: 1 period negative comovement between  $\Delta inv_t$  and  $(c_t, i_t)$ . Dashed line: 1 period positive comovement between  $c_t$  and  $i_t$ .



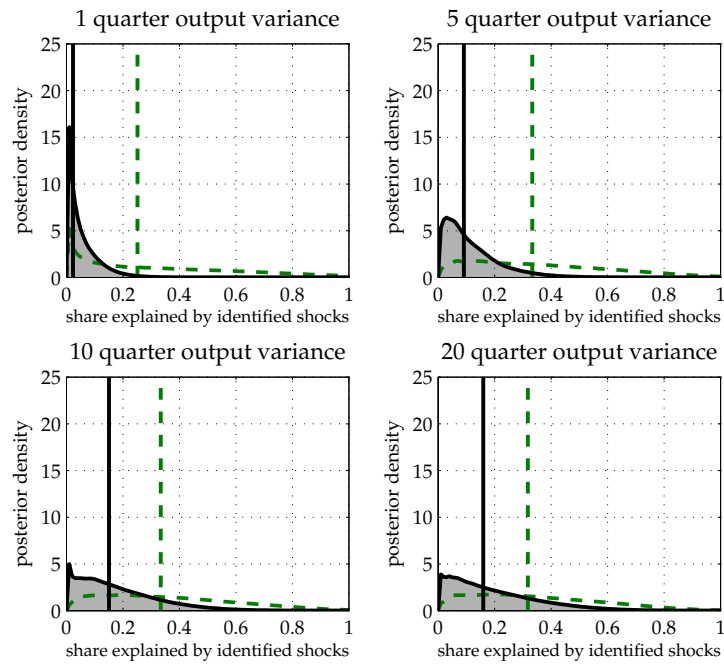


Figure 17: Robustness of forecast error variance 3. Posterior probability density and median (vertical line) for the share of forecast error variance of output at each horizon explained by shocks identified using the alternative output series (without government spending and net exports), with 2 period restrictions. Solid line: 2 period negative comovement between  $\Delta inv_t$  and  $(c_t, i_t)$ . Dashed line: 2 period positive comovement between  $c_t$  and  $i_t$ .

Parameter	Value	Description
$\beta$	0.99	Subjective discount factor
$\sigma$	1	Household intertemporal elasticity of substitution
$\alpha_K$	0.225	Capital share
$\alpha_N$	0.675	Labor share
$\delta_k$	0.025	Capital depreciation rate
$u$	1	Capacity utilization rate
$\mu^Y$	1.0045	Gross per capita GDP growth rate
$\mu^A$	0.9957	Gross investment price growth rate
$G/Y$	0.2	Government consumption to GDP
$n$	0.2	Hours
$\mu$	1.15	Price markup
$\delta_i$	0.025	Inventory depreciation rate
$IS$	0.75	Inventory-sales ratio

Table 5: Calibrated parameters.

## C Details on the structural estimation of section 7

The estimation strategy is Bayesian, and mostly follows section 5 of [Schmitt-Grohé and Uribe \(2012\)](#). Readers should refer to that section for a detailed discussion. In table 5, we present calibrated parameters. Standard parameters follow the values used in [Schmitt-Grohé and Uribe \(2012\)](#), and inventory-specific parameters are discussed in the main paper.

The period of data we use is 1955Q2-2006Q4. For the measurement equations, we use the same 7 observables (output growth, consumption growth, investment growth, hours growth, government consumption growth, productivity growth, investment price growth) as in [Schmitt-Grohé and Uribe \(2012\)](#), where measurement errors are only allowed on output growth. On top of that, we also use the per capita real growth rate of inventories as an additional observable, with measurement errors also allowed on this series. The source of measurement error on inventories is due to different valuations in GDP computation and inventory measurement. That is, real stock of inventories in NIPA are computed by taking the average price during the period, using various valuation methods (FIFO, market value). On the other hand, inventory investment used to produce GDP is computed by the end-of-period price of inventories.<sup>31</sup> We allow for persistence in the measurement error for inventories.

It is important to note that adding data on inventories as an observable is not crucial to

<sup>31</sup>We thank Michael Cortez at the Bureau of Economic Analysis for clarifying this.

Bayesian Estimation							
Parameter	Distribution	Prior			Posterior		
		Median	5%	95%	Median	5%	95%
$1/\xi$	Gamma	3.92	2.51	5.77	1.70	1.13	2.25
$\gamma_h^y$	Uniform	0.50	0.05	0.95	0.00	0.00	0.01
$\phi_y^y$	Gamma	3.92	2.51	5.77	9.23	7.34	10.35
$\delta_k^y/\delta_k^v$	Igamma	0.75	0.32	0.96	0.31	0.24	0.38
$b$	Beta	0.50	0.17	0.83	0.92	0.91	0.94
$\rho_{xg}$	Beta	0.73	0.32	0.96	0.79	0.64	0.91
$\phi_y^y$	Gamma	3.67	1.37	7.75	0.52	0.20	0.87
$\phi_y^{pv}$	Gamma	3.67	1.37	7.75	2.68	2.02	3.28
$\phi_a$	Gamma	3.67	1.37	7.75	0.65	0.21	1.13
$\rho_z^z$	Beta	0.73	0.32	0.96	0.95	0.92	0.97
$\sigma_z^z$	Gamma	1.15	0.27	3.06	0.64	0.54	0.74
$\sigma_z^a$	Gamma	0.66	0.16	1.76	0.12	0.00	0.26
$\sigma_z^g$	Gamma	0.66	0.16	1.76	0.09	0.00	0.21
$\rho_{\mu^A}$	Beta	0.50	0.17	0.83	0.46	0.37	0.55
$\sigma_{\mu^A}$	Gamma	0.24	0.06	0.64	0.18	0.01	0.33
$\sigma_{\mu^A}$	Gamma	0.14	0.03	0.37	0.15	0.04	0.24
$\sigma_{\mu^A}$	Gamma	0.14	0.03	0.37	0.24	0.10	0.32
$\rho_{\mu^A}$	Beta	0.73	0.32	0.96	0.96	0.94	0.99
$\sigma_{\mu^A}$	Gamma	0.81	0.19	2.15	0.71	0.24	1.01
$\sigma_{\mu^A}$	Gamma	0.46	0.11	1.02	0.73	0.48	0.92
$\sigma_{\mu^A}$	Gamma	0.46	0.11	1.02	0.25	0.00	0.70
$\rho_{\mu^X}$	Beta	0.23	-0.18	0.46	0.30	0.17	0.47
$\sigma_{\mu^X}$	Gamma	0.35	0.08	0.94	0.47	0.30	0.63
$\sigma_{\mu^X}$	Gamma	0.20	0.05	0.53	0.08	0.00	0.18
$\sigma_{\mu^X}$	Gamma	0.20	0.05	0.53	0.09	0.00	0.18
$\rho_{\mu^X}$	Beta	0.73	0.32	0.96	0.99	0.98	1.00
$\sigma_{\mu^X}$	Gamma	0.92	0.22	2.45	1.42	0.90	1.80
$\sigma_{\mu^X}$	Gamma	0.53	0.13	1.42	1.57	1.24	1.91
$\sigma_{\mu^X}$	Gamma	0.53	0.13	1.42	0.31	0.00	0.84
$\rho_{\mu^X}$	Beta	0.50	0.17	0.83	0.19	0.11	0.30
$\sigma_{\mu^X}$	Gamma	4.82	1.15	12.87	6.03	1.15	9.13
$\sigma_{\mu^X}$	Gamma	2.78	0.66	7.43	6.10	1.08	8.51
$\sigma_{\mu^X}$	Gamma	2.78	0.66	7.43	3.77	1.17	6.10
$\rho_{\mu^X}$	Beta	0.50	0.17	0.83	0.85	0.77	0.93
$\sigma_{\mu^X}$	Gamma	13.14	3.14	35.07	6.41	4.25	7.89
$\sigma_{\mu^X}$	Gamma	7.59	1.81	20.26	0.68	0.00	1.69
$\sigma_{\mu^X}$	Gamma	7.59	1.81	20.26	1.62	0.01	3.30
$\rho_{\mu^X}$	Beta	0.50	0.17	0.83	0.77	0.71	0.83
$\sigma_{\mu^X}$	Gamma	0.86	0.20	2.29	2.85	2.34	3.31
$\sigma_{\mu^X}$	Gamma	0.50	0.12	1.33	0.63	0.26	0.93
$\sigma_{\mu^X}$	Gamma	0.50	0.12	1.33	0.22	0.00	0.47
$\sigma_{\mu^X}^{me}$	Uniform	0.15	0.02	0.29	0.27	0.25	0.30
$\rho_{\mu^X}^{me}$	Beta	0.50	0.17	0.83	0.21	0.09	0.33
$\sigma_{\mu^X}^{me}$	Uniform	0.15	0.02	0.29	0.30	0.29	0.30

Table 6: Parameter Estimation on US Data. Posterior is the result of estimation with using inventories as an additional observable. Hence 8 observable series (output, consumption, fixed investment, government spending, hours worked, TFP, investment price, inventories) are used. All numbers are rounded. A transformed parameter  $\rho_{\mu^X} + 0.5$  is estimated for  $\rho_{\mu^X}$ .

our estimation. Inventory investment is implicitly included in the existing observables used for estimation (output, consumption, investment and government spending) by the resource constraint (output net of consumption, investment, and government spending is inventory investment in a

Statistic	Y	C	I	N	G	TFP	A	INV
Standard Deviations								
Data	0.91	0.51	2.28	0.84	1.14	0.75	0.41	0.88
Model	0.89	0.63	3.56	0.82	1.08	0.77	0.38	1.39
Correlations With Output Growth								
Data	1.00	0.50	0.69	0.72	0.25	0.40	-0.12	0.44
Model	1.00	0.45	0.59	0.53	0.20	0.47	0.01	0.20
Autocorrelations								
Data	0.28	0.20	0.53	0.60	0.05	-0.01	0.49	0.55
Model	0.39	0.39	0.75	0.21	0.02	0.06	0.46	0.80

Table 7: Model estimation result is based on posterior median estimates. The columns are output (Y), consumption (C), fixed investment (I), hours (N), government spending (G), total factor productivity (TFP), relative price of investment (A), and inventories (INV) all in growth rates.

closed economy). However, in the actual output data, net exports are also included and may potentially mask the dynamics of inventories. By directly including the stock of inventories as an observable, the inventory adjustment mechanism is likely to be more precisely estimated.

Table 6 summarizes the priors and posteriors in the model. Notice that for the priors on the standard deviations, we let the contemporaneous shock account for 75 percent of the total variance of the shocks. That is, priors are set such that news shocks account for 25 percent of the total variance.

Table 7 summarizes the predictions of the model. For standard deviations, most values are close to the data, but for fixed investment and inventories, the standard deviations are about 50 percent higher. Second, the model also predicts that inventories are positively correlated with output growth, with a correlation of 0.21. Lastly, we observe that the model autocorrelation is quite similar to the data, with hours (N) showing the most trouble, which is also discussed in [Schmitt-Grohé and Uribe \(2012\)](#).