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

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Abstract

Are news shocks, which change agents’ expectations about future fundamentals, an important source of business-cycle fluctuations? The existing literature has provided a wide range of answers, finding that news shocks can account for 10 percent to 60 percent of the volatility of output. We show that looking at the dynamics of inventories, so far neglected in this literature, cleanly isolates the role of news shocks in driving business cycles. In particular, inventory dynamics provide an upper bound on the explanatory power of news shocks. We show, for a broad class of theoretical models, that finished-good inventories must fall when there is an increase in consumption and investment induced by news shocks. When good news about future fundamentals lowers expected future marginal costs, firms delay current production and satisfy the increase in demand by selling from existing inventories. This result is robust across the nature of the news and the presence of different types of adjustment costs. We therefore propose a novel empirical identification strategy for news shocks: negative comovement between inventories and components of private spending. Estimating a structural VAR with sign restrictions on inventories, consumption and investment, our identified shock explains at most 20 percent of output variations. Intuitively, since inventories are procyclical in the data, shocks that generate negative comovement between inventories and sales cannot account for the bulk of business-cycle 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 come through changes in expectations and investment (Beaudry and Portier, 2013). For example, when productivity is expected to increase in the future, investment increases to build up the capital stock to take advantage of the lower marginal costs in the future. This boom in investment raises wages and hours worked, and the additional income leads to a consumption boom. Hence good news about future productivity leads to a current boom in output, and investment is a key channel. Recent theories of the business cycle based on news shocks are successful in capturing this mechanism. A prominent example is Jaimovich and Rebelo (2009) where they show that, in a neoclassical growth model with investment adjustment costs, variable capacity utilization, and weak wealth effects on hours worked, an expected rise in the marginal product of capital leads to a boom in investment today. Adding variable capacity and weak wealth effects on hours worked allows output to rise on impact and satisfy current demand, while investment adjustment costs lead firms to smooth the desired increase in the stock of capital over time and start investing today.

However, the empirical literature on estimating the role of news shocks over the business cycle has yet to come to a consensus. While some estimate that news shocks account for as high as 60 percent of output variations, others with equally plausible methods end up with as low numbers as 10 percent. This indicates that the literature is still in need of additional information to precisely characterize the importance of news shocks. The goal of this paper is to bring in new insight that could improve on our empirical characterization of news shocks over the business cycle. To be specific, we focus on a variable that is highly informative about news shocks, but so far has been

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1For example, Beaudry and Portier (2006) and Schmitt-Grohé and Uribe (2012) estimate that the contribution of news shocks to output variations is above 50 percent, while Barsky and Sims (2011) and Khan and Tsoukalas (2012) is small. This will be discussed in detail in later sections.
neglected in the literature: investment in finished-good inventories.

Investment in finished-good inventories is informative in the context of news shocks for the following reasons. First, finished-good inventories are a forward-looking variable that responds to changes in expectations about future economic conditions. For instance, Kesavan, Gaur, and Raman (2010) find that finished-good inventory data are valuable for forecasting sales. Since expectations and investment behavior are at the center of the economic mechanism for how news shocks work, investment in finished-good inventories should be a good source of identification. Second, finished-good inventories provide us a clear differentiation between shocks that happen today and shocks that are expected to happen in the future. A straightforward illustration is when the economy faces temporary changes in productivity. When productivity increases today, then higher income today will raise sales. Firms at the same time will bunch production to make the most out of the productivity increase and finished-good inventories will also rise. Hence with a change in productivity today, there will be positive comovement between inventories and sales. When productivity is expected to increase tomorrow, then higher income in the future will also raise sales today. However, since firms expect future production to be cheaper than current production, they will satisfy this increase in sales by depleting inventories. Hence with a change in productivity tomorrow, there will be negative comovement between inventories and sales.

In section 2, we start our analysis by introducing inventories as in Bils and Kahn (2000) into a news-driven business-cycle model. In section 3, we use this model to show that good news about the future leads to a boom in consumption and investment, but a fall in inventories. The intuition at the heart of our result is that news shocks lead to strong intertemporal substitution in production. 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. Thus, news-induced booms lead to inventory disinvestment, that is, news shocks generate negative comovement between inventories and sales.

In section 4, we show that our result holds in many directions under the baseline model. First, we show that the fall in inventories after a positive news shock is deep and protracted. Second, we establish that our result holds for other types of news, especially news on demand. Third, we

\footnote{From now on, we will use the term “inventories” to indicate finished-good inventories when there is no confusion.}
introduce various types of adjustment costs to check whether our result is robust. In section 5, we show that our result also holds in alternative inventory models, 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). Although each class of models introduce inventories for different reasons, it is important to note that the strong intertemporal substitution channel is a general feature.

Having established that the negative comovement of inventories and sales is a solid outcome of news shocks, we propose to use this prediction as a means to identify news shocks. In section 6, we describe an empirical strategy based on this idea, a structural VAR with sign restrictions. We show that a range of shocks identified in this manner explain less than 20 percent of output variations over the business cycle. The reason we get a small and precise contribution of news shocks is because inventories are procyclical in the data. Hence a shock that generates negative comovement between inventories and sales have limited importance over the business cycle. In section 7, we show that our results also hold in an estimated DSGE model with inventories. Using a stock-elastic demand inventory model and including a wide range of shocks studied in the literature, we estimate news shocks to account for less than 10 percent of output growth variations. Section 8 concludes.

Our work relates to a number of papers that examine the behavior of investment with 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 cost for news shocks to generate an immediate boom in investment and output. However, 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. These type of inventories do not enter the production function, and therefore the previous channels through which investment operates under news shocks no longer applies. Our contribution to the news literature then is to illustrate a new channel through which news shocks operate by focusing on the investment behavior of finished-good inventories that is distinctive from capital investment.

Our work also relates to the recent literature on inventories that matches the stylized business-cycle facts of inventories with micro foundations at the firm level. The main difference across these models is how they generate a positive level of inventories at the steady state. To be specific, one
branch of the literature argues that inventories exist since they facilitate sales either by their use for displaying and advertising purposes (Bils and Kahn, 2000), or by their use for 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 fit better into the former approach. Nevertheless, our result also applies to the latter approach, since a common feature of all these models is that inventories are producers’ means of intertemporal substitution. Our contribution to this literature is highlighting this common mechanism of a wide range of inventory models when business cycles are driven by news shocks.

Lastly, our empirical approach is based on the sign restriction literature in a vector autoregression (VAR) framework. These approaches have been applied in identifying 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 lay out 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 us a clear intuition on how inventories work in the economy in response to news shocks. Other models will be discussed in later sections.

The key feature of the stock-elastic demand model we analyze in 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. This may arise either because of greater availability of goods, or because more on-shelf goods may provide a wider variety within the same product. For example, a shoe store with more colors and size of all kinds are likely to attract more customers and sell more goods.

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3See Khan and Thomas (2007a) for a comparison between 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,

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

where \( c_t \) is the consumption of the final good, \( n_t \) denotes the supply of labor services, and \( \psi_t \) is an 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):

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

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:

\[ \int_0^1 p_t(j) s_t(j) dj + E_t [Q_{t,t+1} B_{t+1}] \leq W_t n_t + R_t k_t + \int_0^1 \pi_t(j) dj + B_t, \tag{2} \]

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

\[ c_t + i_t \leq x_t. \tag{4} \]

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 accumulation rule of capital with adjustment costs to investment. The adjustment cost function $\phi(\cdot)$ is twice-differentiable with $\phi(1) = \phi'(1) = 0$, and $\phi''(1) > 0$. Adjustment costs of this form generate an immediate build-up motive for capital when the desired level of capital is high in the future.

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:

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

(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 amounts of goods on shelf proposed by the firm producing variety $j$, $a_t(j)$, in the following fashion:

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

(6)

where the normalization by $a_t$, defined as the economy-wide average of on-shelf goods, ensures that the mean of $v_t(j)$ 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

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

where

\[
\pi_t(j) = p_t(j) s_t(j) - W_t n_t(j) - R_t k_t(j).
\]

Note that 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 bonds 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:

\[
a_t(j) = (1 - \delta_t) inv_{t-1}(j) + y_t(j),
\]

\[
inv_t(j) = a_t(j) - s_t(j),
\]

\[
y_t(j) = z_t k_t^{1-\alpha}(j)n_t^\alpha(j),
\]

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

Equation (9) is the 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 \( (1 - \delta_t) inv_{t-1}(j) \) and current production \( y_t(j) \). The parameter \( \delta_t \) denotes the depreciation rate of inventories. Equation (10) states that on-shelf goods that are unsold are accounted as inventories.\(^4\) 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.

\(^4\)In the data, this is recorded as the end-of-period inventory stock in each period.
Market clearing  Labor and capital markets clear, and the net transaction of bond 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 by the demand function described above. The average 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).\footnote{Other types of shocks will be discussed in later sections.}

2.3 The optimal choice of inventories

The full set of equilibrium conditions are provided in the online appendix. As we show there, 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:

\[
mc_t = \frac{W_t}{\alpha z_t (k_t/n_t)^{1-\alpha}}. \tag{17}
\]

Using this, the optimal stock choice of firms is governed by the equation:\footnote{Here, \( q_{t,t+1} = Q_{t,t+1} P_{t+1}/P_t \) denotes the real stochastic discount factor of the household.}

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

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 \( \frac{\partial s_t}{\partial a_t} \) of sales. Second, since some of these additional stock of goods will not be sold and will be stored as inventories for the next period, future production cost reduces.

It is important to notice that at the nonstochastic steady state of the economy, the stock of inventories are positive. Since the real interest rate and the inventory depreciation rate are both positive at the steady state, holding inventories over time is a loss. However, consistent with the first term on the right hand side of \( (18) \), there is a convenience yield in 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, even with the cost over time, the economy will hold a positive level of inventories at the steady state to maintain their level of sales.
Rearranging, (18) can be expressed as:

\[
\frac{\partial s_t}{\partial a_t} = \frac{\gamma_t^{-1} - 1}{\mu_t - 1},
\]

where:

\[
\mu_t \equiv \frac{1}{(1 - \delta_t)E_t[q_{t,t+1}mc_{t+1}]}, \quad \gamma_t \equiv (1 - \delta_t)E_t \left[ \frac{q_{t,t+1}mc_{t+1}}{mc_t} \right].
\]

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 the benefit of stocking in generating sales.

In equilibrium, the optimal choice of inventories expressed in a first-order log-linear approximation around its steady state is:

\[
\hat{\text{inv}}_t = \hat{s}_t + \eta \hat{\gamma}_t,
\]

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, where firms in this economy build in their inventories when sales are high. For example, when there is an increase in aggregate demand, then 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, \( \eta \) represents 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.

\footnote{This equation is derived by combining (10), (19) and the optimal pricing condition \( \hat{\mu}_t = 0 \).}
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. When the value of $\eta$ is infinitely large, then the degree of intertemporal substitution is so large that even a small change in the perception of the marginal cost will result in a massive change in inventories.

Hence the optimal decision of inventories in our model depends on the relative strength between 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 them.

#### 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 analysis on inventories and news shocks.

**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:

1. $\hat{m}_t = \omega \hat{y}_t$, \quad (20)
2. $\kappa \hat{y}_t = \hat{s}_t + \frac{\kappa - 1}{\delta_i} \text{inv}_t - (1 - \delta_i) \text{inv}_{t-1}$, \quad (21)
3. $\text{inv}_t = \hat{s}_t + \tau \hat{\mu}_t + \eta \hat{\gamma}_t$, \quad (22)
4. $\hat{\mu}_t = 0$, \quad (23)
5. $\hat{\mu}_t + \hat{\gamma}_t + \hat{m}_t = 0$. \quad (24)
The mapping from the structural model parameters to the parameters of the reduced-form equations is given by:

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

\[
\kappa = 1 + \delta IS, \quad (26)
\]

\[
\eta = \frac{1 + IS}{IS - 1 - \beta(1 - \delta)}, \quad (27)
\]

\[
\tau = \theta \frac{1 + IS}{IS},
\]

where \( IS \) is the steady-state inventory-sales ratio, given by

\[
IS = \frac{(\theta - 1)(1 - \beta(1 - \delta))}{\zeta\beta(1 - \delta) - (\theta - 1)(1 - \beta(1 - \delta))}.
\]

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 we consider a range of values. In fact, 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. In its log-linearized form, \( \kappa \) 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 of \( \eta \) 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 extreme 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 extreme case when 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.\(^8\) With a rather high value of \( \delta_i = 0.04 \), the lower bound is

\[ \eta > 20. \]

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 \( \hat{inv}_t \), 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 has no impact on current fundamentals (\( \hat{z}_t = 0 \) and \( \hat{\psi}_t = 0 \)), but future fundamentals are expected to change (\( \mathbb{E}_t \hat{z}_{t+k} \neq 0 \) or \( \mathbb{E}_t \hat{\psi}_{t+k} \neq 0 \) for some \( k > 0 \)).

\(^8\)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 arrives, 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 depend on three parameters: $\kappa$, $\omega$ and $\eta$. With $\kappa = 1.005$, the two parameters $\omega$ and $\eta$ need to be sufficiently small for positive comovement between inventories and sales. 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 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 production of the firm. Therefore, inventories are less important as means of intertemporal substitution of production. In this economy, 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.
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.\(^9\) In the extreme case with zero intertemporal cost of adjusting inventories, we see that the degree of intertemporal substitution, $\eta$, reaching 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.

To summarize, since standard calibrations suggest a small cost of adjusting goods across time, the model does not predict an inventory boom when there is a sales boom in response to news shocks.

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. We found that news shocks generate negative comovement between inventories and sales. We now turn to several extensions of this result. We first show that the negative comovement between inventories and sales holds beyond impact and whether allowing variable capacity utilization changes our result. Second, we study inventory behavior with surprise shocks to confirm that the negative comovement property is an identifying feature of news shocks. Third, we study the comovement property with other types of news shocks. Fourth, we check the robustness of our result by introducing different types of adjustment costs.

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

4.1 Calibration

The numerical values for the parameters are summarized in table 1. Standard model parameters are calibrated using estimates from the business-cycle literature. Parameters specific to the

\(^9\)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.
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 each shocks, $\rho_z = 0.99$ and $\rho_\psi = 0.95$ are assumed.\textsuperscript{10}

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.\textsuperscript{11}

Figure 2 reports the impulse responses. Note first that consumption and investment, which are components of sales, increase immediately, and throughout the realization of the shock. Consumption increases because of the wealth effect associated and investment increases because of the presence of investment adjustment costs.

In line with our discussion of the previous sections, inventories fall. The fall is large and persistent, and reaches its trough in the period preceding the realization of the shock. At the same time, output remains mostly unchanged until period 4, when the shock realizes. That is, the increase in sales during the news period is almost entirely met by inventory disinvestment. To build further intuition for the responses of inventories, note that the optimal labor supply and demand schedule in an economy with inventories is:

\begin{equation}
\psi_t n_t^{1/2} = \alpha mc_t z_t k_t^{1-\alpha} n_t^{\alpha-1},
\end{equation}

(28)

so that marginal cost is given by:

\begin{equation}
\hat{mc}_t = \omega \hat{y}_t - \hat{z}_t + \hat{\psi}_t - (\omega + 1) (1 - \alpha) \hat{k}_t.
\end{equation}

(29)

This marginal cost equation tells us that both news about an increase in future productivity and

\textsuperscript{10}These estimates of persistence are close to the empirical findings in the literature.

\textsuperscript{11}We define a positive news shock by a shock that generates an increase in sales. When labor wedge is expected to decrease, then households expect to face less disutility of working in the future and this will also boost current sales.
news about a decrease in future labor wedge are declining forces to the 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 we see from 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 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 and see whether our result remains. Denoting $u_t$ as the utilization of capital at period $t$, the production function and the capital accumulation function are modified respectively as follows:

\[
y_t = z_t (u_t k_t)^{1-\alpha} n_t^\alpha,
\]
\[
k_{t+1} = (1 - \delta(u_t)) k_t + \left[ 1 - \phi \left( \frac{i_t}{i_{t-1}} \right) \right],
\]

where $\delta'(\cdot) > 0$ and $\delta''(\cdot) > 0$. In words, higher utilization of capital increases output, but this comes at a cost of higher depreciation of capital. In a model without inventories as in 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:

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

With inventories, the increase in consumption and investment can be matched by depleting inventories rather than working more. Therefore, $n$ does not go up with an increase in $c$, which generates a steeper fall in the marginal value of income. Hence even with capacity utilization, the economy does not ask for more production at the expense of depreciating installed capital since their utility level is already high. Again, we confirm that our negative comovement between inventories and sales in response to news shocks is an equilibrium outcome even with sufficient channels for production to increase.

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). The model prediction is thus broadly consistent with the observed behavior of inventories

\[\text{The countercyclicality of the inventory-sales ratio is not completely robust to the calibration of the shock, as it depends partly on the magnitude of the initial increase in sales. For a smaller persistence of productivity shocks of...}\]
and sales over the business cycle. Thus, the negative comovement of inventories and sales is an identifying feature of news shocks to fundamentals.

4.4 Other types of news shocks

Although the two types of shocks we have considered up to now are argued as 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. Then they will consume less today since they now discount the future 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 the two shocks discussed.\textsuperscript{13} As discussed, the negative comovement property is also true with these two types of shocks.

\textsuperscript{13}The persistence of each process are 0.17 for the discount factor and 0.95 for the spending. These values come from Schmitt-Grohé and Uribe (2012).
4.5 Adding adjustment costs

Adding adjustment costs to capital investment has been a key element for generating an investment boom with news shocks (Jaimovich and Rebelo, 2009). Capital is slow to adjust, and with this form of adjustment cost, investment decisions depend solely on the discounted sum of future marginal values 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.

This logic does not extend to inventory investment, in particular for 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 cost to finished-good inventory investment is a less appealing approach.

However, adjustment cost to the stock of inventories may have a better justification: 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 help us. We consider three possible types of adjustment costs: adjustment costs to inventories, output and on-shelf goods. Adjustment cost to inventories penalizes immediate inventory depletion and thus weakens the intertemporal substitution motive. Adjustment cost 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 cost to goods on shelf are 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 are modified as follows:

\[ inv_t = (1 − δ_t)inv_{t−1} + y_t − s_t − ADJ_t, \]
where $ADJ_t$ is the adjustment cost of each type. We assume the following form:

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

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, where output adjustment cost is assumed. 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.

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 not only to compensate for the current loss of utility by working more, but also to increase their level of utility with their higher income.

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 these other models that illustrate important margins of inventory adjustment discussed in the business-cycle literature. In the leading business-cycle models, inventories are introduced either as buffers to uncertainties in demand at the firm level (stockout-avoidance models), or as economies of scale due to nonconvex delivery costs at the firm level (Ss inventory models). We will focus more on the first approach since they fit better for finished-good inventories (Khan and Thomas, 2007a). Nevertheless, we also discuss the second approach for completeness.

For a preview, it turns out that our result remains 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 on the marginal cost profile. Since news shocks directly affect this perception, the other margins which differ across models matter less, in particular close to the moment when the news shock is expected to realize in the next period.

5.1 Stockout-avoidance model

One branch of the literature on finished-good inventories motivates inventories by introducing a lag in production and the realization of sales. Since production decisions are made with uncertainty in demand, inventories are buffers to the possibility of stocking out. In these stockout-avoidance models, firms are assumed to have imperfect information on the demand schedule for their variety at the time they make decisions. When 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.\footnote{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 dataset are roughly 5 percent. More recently, using supermarket-level data for a large retailer, Matsa (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.}

In a separate 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. This follows from obtaining analytical restrictions on reduced-form parameters to precisely quantify the conditions under which this result holds. 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 cost, 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 benefit of stocking is twofolds: (i) In the case that sales turn out high, then the firm can increase its sales by producing an additional product. (ii) In the case that sales turn out low, then...
the firm can save its future production cost by stocking it as inventories. It turns out that even in this class, the intertemporal substitution motive is quantitatively stronger for news shocks.

5.2 \((S,s)\) inventory model

Although the focus has been more on input inventories, the existence of nonconvex delivery costs at the firm level has also been claimed as an important reason for the presence of inventories. In the model of Khan and Thomas (2007b), the firm pays a fixed cost when placing an order for inputs. This cost comes at a random manner, and there is a distribution of firms with different levels of inventories. In this model, the optimal stocking condition for stock adjusting firms is also a balance between the cost and benefit of ordering goods as we discussed in (18). To be precise, the cost of stocking is the total cost of goods and a fixed delivery cost. The benefit of stocking is twofolds: (i) In the case when future delivery cost turns out high, then firms will not order at that time. Then the total production capacity of the firm is 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 the case when future delivery cost turns out low, then firms can order at that time as well. In this case, the firm will save its total cost if they expect that the unit cost of good will be expensive 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 cost of input inventories is also cheaper. We solve for the perfect foresight transition dynamics with a news shock to productivity in Khan and Thomas (2007b).\(^{15}\) We plot the response of inventories in figure 8, along with the two other classes of models we discussed so far. All models share in common that inventories fall, especially right before the realization of the shock. Therefore, we conclude that the strong intertemporal substitution channel with news shocks is a common feature across all models.

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. Indeed, as we have discussed at length, it holds for all

\(^{15}\)Refer to Khan and Thomas (2007b) for the solution algorithm.
plausible calibrations of the models. In this section, we use this structural restriction to estimate the importance of news shocks.

The approach we take in this section is estimating 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 could remain agnostic in other aspects, and therefore robustly identify shocks without other misspecification concerns. On the other hand, the loss of this approach is that identification is weak since we may be including 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 use 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.\textsuperscript{16}

6.2 Baseline specification and estimation

Our baseline identification strategy imposes that on impact, there is disinvestment in inventories, whereas consumption and fixed investment increases.\textsuperscript{17} The VAR model we estimate is the following:

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

\textsuperscript{16} The source of the data is NIPA table 1.1.5 and 5.7.6.
\textsuperscript{17} 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.
For $X_t$, we use log levels of each variable to be robust to cointegrating relations. We estimate with a constant term and four lags.\footnote{The Schwartz information criterion suggests two lags but our results are not sensitive to the number of lags.} We estimate the model using 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.\footnote{Our result to follow is not sensitive to adding more draws.}

6.3 Baseline result

Figure 9 reports the posterior distribution of the FEV of our identified shocks on output, for different horizons.\footnote{As noted above, we plot the case for nonfarm private inventories but the plot is similar with retail trade inventories as well.} The posterior has a sharp mode close to zero, and the median is close to 20 percent in most horizons. In figure 10, we plot the set of identified impulse responses. We see that the median characteristic of 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 inventories become positive after 3 quarters. Notice that in our model, this is also the case when good news is expected to realize in the near future. Therefore, the average characteristic of 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 among short and long-horizon news shocks. Since the focus of the news literature is not on one or two quarter news shocks, but rather on the long horizon, 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 by simulated data from an estimated medium-scale DSGE model.\textsuperscript{21} In particular, we add a standard inventory approach to an estimated model of Schmitt-Grohé and Uribe (2012), and simulate the impulse responses for different horizons of news shocks. 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 in the model.

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

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

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 $\tau = (\zeta - \zeta)/\zeta$, which is the steady-state inventory-sales ratio.

In table 3, we show the success probability of our identification approach with different horizons of news shocks.\textsuperscript{22} For the shocks we consider, our dynamic restriction is successful in identifying longer horizon news shocks.

6.5 Estimation result and discussion

Figure 11 reports the posterior distribution of the FEV of our identified shocks on output, where inventory disinvestment occurs for 2 periods, and at the same time both consumption and investment are above the steady state for 2 periods. We see that the posterior has a sharp mode close to zero, and the median is now close to 10 percent in all horizons, about half smaller than

\textsuperscript{21}This part may be skipped if the reader finds the claim to be straightforward.

\textsuperscript{22}We focus on the stationary shocks in Schmitt-Grohé and Uribe (2012). We exclude investment specific shock since with our model has two types of investment, and 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, and this will also have affected capital goods.
the result with impact restrictions only. To get a sense of the information that inventories deliver, figure 11 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 12 reports the impulse responses of 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 increases, but the increase in output is now modest.

We also extend our dynamic restriction to 3 periods, that is 3 period inventory disinvestment and at the same time 3 period increase in consumption and fixed investment. As in figure 13, 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 variations. Figure 14 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 in 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 in all horizons.

The reason why FEV turns out small is because inventories are a procyclical variable. In the data, the unconditional contemporaneous correlation between inventories and sales (consumption plus investment) is 0.50.\(^{23}\) Since our identification is based on negative comovement of these comoving variables, there is a limit to which the contribution of these shocks would be able to generate a large bulk of business cycles.

\(^{23}\)This is based on HP filtered data but the result is not sensitive to filtering methods.
6.6 Robustness

Since our identifying assumption is only on the sign responses of inventories and components of sales, it is robust to changes in specification. However to make sure that our result does not break down under some conditions, we have nevertheless performed robustness checks in several dimensions. First, we used different priors for the coefficients such as the Minnesota prior or the Normal-Wishart prior. None of these specifications have significant effects. Second, when imposing our dynamic restriction, we also tried to be less restrictive by not imposing the negative comovement on impact or second period, to control for any demand effects that 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 at 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 result is not sensitive to this. This suggests that the cyclical property of inventories and sales in terms of the sign responses did not change a lot around this period.

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), or combining them also with data on stock price (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

[24]Since our focus is mainly on the forecast error variance, it might be more desirable to set a uniform prior directly on this moment. However, forecast error variance is a highly nonlinear transformation of the VAR coefficients, hence existing methodologies do not allow us easily solve the inverse problem to back out the implied prior for the coefficients. As a way to overcome this issue, we are showing our result with and without the negative comovement assumption to control for the prior.
is by looking into movements in stock prices orthogonal to any changes in current productivity. To understand the movements of inventories in this estimation strategy, we ran a 3 variable VAR with utilization-adjusted productivity, S&P 500 index as stock prices, and inventories. We imposed impact zero restriction on productivity, and saw the dynamics of inventories when stock prices increase, which is consistent with a boom in consumption and investment (Beaudry and Portier, 2006). In response to a range of shocks, we found that the sign of the impact and short-run responses of inventories are inconclusive.\textsuperscript{25} This suggests that existing methods are not fully incorporating the information inventories provide in response to news shocks.\textsuperscript{26} This is linked to the fact that existing literatures provide a wide range of numbers for the contribution to output volatility. For instance, 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) find 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. 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 by Bayesian methods to test whether news shocks are important. The purpose of this section is twofold. First, while the agnostic VAR method uses the necessary inventory information in capturing news shocks, they are still partial identification strategies. 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.

With these desirable aspects, it is still 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, since the key prediction of our theory was robust to

\textsuperscript{25}This plot will be in the online appendix.

\textsuperscript{26}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.
several specifications. However, to estimate a DSGE model, we need to select a specific model to estimate. Hence the results coming out of this section are subject to higher 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). Hence the model we estimate is similar to that of section 2, and details of the model are described in the online appendix. However, there are several differences that are worthwhile to mention here.

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

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

\[ s_t(j) = \left( \frac{a_t(j)}{a_t} \right)^{\zeta_t} \left( \frac{p_t(j)}{P_t} \right)^{-\theta_t} x_t, \]

where \( \zeta_t \) and \( \theta_t \) are assumed to be AR(1) processes.\(^{27}\)

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.

### 7.2 Estimation result

Table 4 summaries the variance decomposition of the estimated model. We find that news shocks estimated in this model account for only 5 percent of output variations. This contrasts the result in a model without inventories where 41 percent of output variations were explained 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 consumption, fixed investment and hours worked. For all these variables, news shocks now account for less than 10 percent of total variations. This is also linked to inventory dynamics in the model. We observe that only 7 percent of variations of inventories are accounted for by news shocks.

\(^{27}\)For \( \theta_t \), we transform it into the markup \( \mu_t = \theta_t/(\theta_t - 1) \) and assume this as an AR(1) process.
shocks. The only exception is government spending. Consistent with Schmitt-Grohé and Uribe (2012), we find that news shocks mostly account for the government spending process. In fact, we find that 89 percent of the variation in government spending comes through news shocks.

To sum up, we find that besides government spending, news shocks now account for less than 10 percent of business cycle fluctuations.

8 Conclusion

In this paper, we studied the response of inventories to news shocks. We established conditions on model 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. 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 find 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 variations. 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


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Tables and figures

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<tr>
<th>Parameter</th>
<th>Value</th>
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Table 1: Calibration of the stock-elastic demand model.

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

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Table 3: Success probability of identifying assumption
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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.)
Figure 1: In the stock-elastic demand model, the value of $\eta$ as a function of $1 - \beta(1 - \delta_i)$, holding fixed all the other structural parameters.

Figure 2: Impulse responses to 4-period news shocks in the stock-elastic demand model. Solid line: news on productivity; dashed line: news on labor wedge. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.
Figure 3: Impulse responses to 4-period news shocks in the stock-elastic demand model with variable capacity utilization (utilization parameter: $\delta_k(w) = 0.34$). Solid line: news on productivity; dashed line: news on labor wedge. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.

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

Figure 6: **Impulse responses to 4-period news shock on productivity in the stock-elastic demand model.** 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.
Figure 7: The value of $\eta$ in the stockout-avoidance model, as a function of $1 - \beta(1 - \delta_i)$, holding fixed all the other structural parameters. For comparison $\eta$ for the stock-elastic demand model, same as figure 1, is also plotted.

Figure 8: Impulse responses to 4-period news shock on productivity, across the three class of models. The time unit is a quarter. Impulse responses are reported in terms of percent deviation from steady-state values.
Figure 9: Posterior probability density and the median (vertical line) for the share of forecast error variance of output at each horizon explained by identified shocks, with impact (1 period) restriction.

Figure 10: Median and 80% credible set impulse responses of the identified shock with impact (1 period) restriction.
Figure 11: Posterior probability density and median (vertical line) for the share of forecast error variance of output at each horizon explained by identified shocks, 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 $i_t$.

Figure 12: Median and 80% credible set impulse responses of the identified shock with 2 period restrictions.
Figure 13: Posterior probability density and median (vertical line) for the share of forecast error variance of output at each horizon explained by identified shocks, with 3 period restrictions. Solid line: 3 period negative comovement between $\Delta \text{inv}_t$ and $(c_t, i_t)$. Dashed line: 3 period positive comovement between $c_t$ and $i_t$.

Figure 14: Median and 80% credible set impulse responses of the identified shock with 3 period restrictions.