Inventories and the Role of Goods-Market Frictions for Business Cycles

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Abstract

An important part of fluctuations in aggregate output is due to changes in the stock of inventories. However, the possibility that firms may fail to sell all produced goods and inventory accumulation are typically ignored in business cycle models. Using US data, the "ability to sell" is shown to be strongly procyclical. By including both a goods-market friction and a standard labor-market search friction, the model developed here can—in principal—substantially magnify and propagate shocks, without relying on sticky prices or sticky wages. Despite its simplicity, the model can also replicate key inventory facts. However, when these inventory facts are used to discipline the choice of parameter values, then the analysis indicates that goods-market frictions are quantitatively not that important.

Key Words: Matching models, search frictions, magnification, propagation.

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1 Introduction

Firms are likely to hold back on hiring workers when demand for their products is low and consumers may very well postpone purchases when they worry about becoming unemployed. Such interaction between goods-market and labor-market frictions could deepen economic downturns. In modern business cycle models, such "Keynesian" interaction is typically due to nominal frictions, that is, due to the presence of sticky prices and wages: When prices are sticky, changes in demand have a stronger impact on production and changes in production have a stronger impact on employment when wages are sticky. This paper develops a business cycle model in which such Keynesian interaction is due to the presence of *real* frictions in both the labor market and the goods market. With frictions in both markets, there is a potentially powerful interaction between the goods market and the labor market, *even* when prices and wages are flexible. This paper is related to the coordination failure literature, but does not rely on self-fulfilling expectations nor on multiple equilibria.[1]

It is common to incorporate labor-market search frictions in business cycle models and this approach is adopted here as well.[2] Recently, several papers have incorporated goods-market search frictions into business cycle models.[3] Several of these papers assume that prices are flexible and by doing so make clear that Keynesian interaction between goods and labor markets is possible without relying on price rigidities. This paper shares with the recent literature the assumptions that (i) firms face frictions in finding buyers for their products and (ii) the severity of this friction varies over the business cycle.[4] A minor deviation from the approach followed in the literature is that the goods-market friction affects firms' ability to sell, *not* the ability of consumers to get what they want.

[1] See Cooper (1999) for an overview of coordination failure models.

[2] Merz (1995), Andolfatto (1996), and Den Haan, Ramey, and Watson (2000) are early examples of papers that incorporate labor market search frictions in business cycle models.

[3] For example, Arsenau (2007), Gourio and Rudanko (2011), Mathä and Pierrard (2011), Petrosky-Nadeau and Wasmer (2011), Bai, Ríos-Rull, and Storesletten (2012), Kaplan and Menzio (2013), and Michaillat and Saez (2013).

[4] See Michaillat and Saez (2013) for a detailed discussion of the frictions that firms face when trying to sell their products.

Consequently, Keynesian results in this paper do not rely on the cyclicality of consumers' effort to acquire goods.[5]

A more essential aspect in which this paper differs from the literature is that the model developed here includes inventories. There are several reasons to include inventories. As documented in this paper, the observed behavior of inventories is very informative about the characteristics of frictions in the goods market and the quantitative importance of such frictions for business cycles.[6] This is not surprising. When there are cyclical changes in the frictions that firms face in selling products, then this is likely to affect the accumulation of inventories. Another important reason to include inventories in business cycle models is that changes in the investment in inventories are a quantitatively important aspect of cyclical changes in GDP. Blinder and Maccini (1991) document that the drop in inventory investment accounted on average for 87 percent of the drop in GNP in the postwar US recessions they considered. This paper confirms the empirical relevance of changes in investment in inventories for cyclical fluctuations in GDP, although the estimates are not as high as the one reported in Blinder and Maccini (1991).

This paper makes four contributions. First, the paper constructs a measure of "goods-market efficiency" and documents its properties. Second, the paper develops a business cycle model with inventories that is characterized by frictions in the labor *and* the goods market. Third, the paper documents that the model can match key aspects of US business cycle and in particular the cyclical behavior of inventories. Fourth, the paper documents the importance of goods market frictions when the model is consistent with the cyclical behavior of inventories. These contributions are discussed in more detail in the remainder

[5] It is not clear whether consumers' effort to acquire goods is procyclical or countercyclical. In the models of Petrosky-Nadeau and Wasmer (2011) and Bai, Ríos-Rull, and Storesletten (2012), consumers put in *less* effort trying to acquire goods during recessions, which is bad for firms. In the model of Kaplan and Menzio (2013), unemployed consumers have more time to allocate to activities unrelated to working. Consequently, consumers put in *more* effort to acquire goods during recessions, since there are more unemployed during recessions. In the model of Kaplan and Menzio (2013), it is bad for firms if consumers put in more effort, since this means that consumers can visit more stores and bargain for lower prices.

[6] The model developed in Michaillat and Saez (2013) does not have inventories, but the paper also points out that there is a link between goods-market frictions and inventories.

of this section.

The measure of goods-market efficiency used is the amount of goods sold relative to the sum of newly produced goods and beginning-of-period inventories. A higher value means that firms sell a higher fraction of available products. This sell probability is a simple transformation of the inventory-sales ratio; if the inventory-sales ratio decreases (increases), then the goods-market efficiency measure increases (decreases). Section 2 documents that this measure of goods-market efficiency is strongly procyclical. This is not surprising given that the inventory-sales ratio is known to be countercyclical and the two measures are inversely related.[7] A novel empirical finding is that the goods-market efficiency measure is negatively related to the beginning-of-period stock of aggregate inventories. This last aspect of goods-market efficiency turns out to play a key role in matching the observed behavior of inventories with the theoretical model.

The empirical findings provide the motivation for the specification of the goods-market friction that firms face in the theoretical model developed. Consistent with the observed positive dependence of the goods-market efficiency on aggregate real activity, the paper follows Diamond (1982) and lets goods-market efficiency vary with market size. The idea is that market participants are more likely to find a trading partner with the desired product in larger markets.[8] The model incorporates this externality, but the externality is not strong enough to generate multiple equilibria as in Diamond (1982). Additional empirical support for this externality is given in Gavazza (2011); using transactions data for commercial aircraft markets, Gavazza (2011) shows that trading frictions diminish with the thickness of the market. In addition, goods-market efficiency is assumed to decrease when aggregate inventories increase, as indicated by the empirical analysis. Except for the presence of inventories and a goods-market friction, the model is a standard business cycle model with a labor-market search friction.

The model can match key facts regarding the behavior of inventories. Important facts

[7] Bils and Kahn (2000) document that the inventory-sales ratio is countercyclical.

[8] The idea is that sellers offer different types of products and that the chance of producing goods that customers do not want is smaller in bigger markets. That is, as the market grows, the law of large numbers becomes more appropriate and uncertainty about the outcome and the chance of mismatch become smaller.

regarding the joint behavior of inventories and real activity are that sales are *less* volatile than production, investment in inventories is *pro*cyclical, and the investment in inventories is *positively* correlated with sales.[9] These properties have surprised the profession because they are inconsistent with the view that firms smooth production and use inventories as a buffer against unforeseen shocks to sales. Building models that can match the facts turned out to be a challenging exercise. There are now several ingenious business cycle models that are consistent with observed behavior, but successful inventory models tend to be characterized by non-trivial features such as Ss bands.[10] In contrast, the model in this paper is extremely simple and can also match the facts. In existing models, the accumulation of inventories is a non-trivial choice problem for the firm. In the model of this paper, firms always try to sell *all* available goods and goods end up in inventories only because firms are not successful in selling goods. Firms could in principle choose to accumulate *additional* inventories, but it is never optimal to do so. To match the inventory facts, the behavior of the goods-market efficiency measure has to be consistent with its observed properties. In particular, both the observed positive dependence on aggregate real activity *and* the observed negative dependence of the goods-market efficiency measure on aggregate inventories are necessary. The simplicity of the approach to model inventories would make it possible to incorporate it in a broad range of business cycle models and by doing so include an important factor behind cyclical changes in aggregate output into the analysis.

The model is used to assess the importance of the goods-market friction for magnifying and propagating shocks when prices and wages are flexible. The paper documents that the procyclical aspect of the goods-market efficiency measure can create a powerful mechanism to magnify and propagate shocks. This is not too surprising, since Diamond (1982) shows that multiple equilibria are possible if the dependence of the goods-market friction on aggregate activity is strong enough. A more interesting question is whether

[9] See Blinder and Maccini (1991), Ramey and West (1999), Bils and Kahn (2000), and McMahon (2011) for a discussion.

[10] Exemplary papers on this road towards success are Eichenbaum (1989), Ramey (1991), Bils and Kahn (2000), Coen-Pirani (2004), and Khan and Thomas (2007).

cyclical changes in goods-market efficiency are still important when the model is consistent with observed inventory facts. The answer is no for two reasons. The first reason is that the positive dependence of goods-market efficiency on aggregate activity cannot be too strong. Consider a shock that negatively affects real activity. If the goods-market efficiency, i.e., the ease with which firms can find customers, drops a lot during economic downturns, then inventories would increase during recessions and not decrease, as they do in the data, and sales would drop by more than output and not by less, as they do in the data. The second reason is that the negative dependence of the goods-market efficiency measure on aggregate inventories also plays an important role in matching key inventory facts. This negative dependence means that cyclical changes in goods-market efficiency are short-lived. That is, following a negative shock, goods-market efficiency deteriorates initially, but it recovers quickly as the stock of inventories is reduced. The last section of the paper discusses some reasons why cyclical changes in goods-market efficiency may still be important, but the conclusion of this paper is that the observed behavior of inventories suggests that interaction between goods-market frictions and labor-market frictions may not be that important, at least not in the type of model considered here and when prices and wages are flexible.

The remainder of this paper is organized as follows. Section 2 describes the goods-market efficiency measure used, its relationship to the inventory-sales ratio, and describes key aspects of its observed cyclical behavior. Section 3 describes the model. Section 4 motivates the parameter choices. Section 5 discusses the results. The last section concludes.

2 Empirical motivation

This paper focuses on the role of cyclical fluctuations in the efficiency of the process to get produced products into the hands of buyers. This section documents the cyclical behavior of this "goods-market efficiency" and links the results to known properties of the cyclical behavior of inventories.

2.1 Goods-market efficiency

Let Y_t be total production in period t and let X_{t-1} be the stock of inventories carried over from the last period after depreciation. The maximum that could be sold in period t is equal to $Y_t + X_{t-1}$. Actual sales, S_t, are typically less. One reason is that goods that are ready to be sold do not find a buyer in the current period. Another reason is that some finished goods have not ended up on store shelves yet and are not ready to be sold. Finally, sales will also be less than $Y_t + X_{t-1}$ if X_{t-1} includes unfinished goods.

Goods-market efficiency, $\pi_{y,t}$, is defined as

$$\pi_{y,t} = \frac{S_t}{Y_t + X_{t-1}}. \tag{1}$$

This measure describes how many goods are sold relative to the sum of newly produced goods and the amount of goods carried over as inventories from last period. The amount sold, S_t, is equal to output minus the investment in inventories. That is,

$$S_t = Y_t - \left(X_t^{\text{eop}} - X_{t-1}\right), \tag{2}$$

where X_t^{eop} is the level of inventories at the end of period t, before depreciation. Combining the last two equations gives

$$\pi_{y,t} = \frac{S_t}{S_t + X_t^{\text{eop}}} = \frac{1}{1 + X_t^{\text{eop}}/S_t}. \tag{3}$$

That is, goods-market efficiency is inversely related to the inventory-sales ratio and both measures can be interpreted as measures that describe the efficiency of getting products in the hands of the customer.[11]

2.2 Cyclical properties of goods-market efficiency

The analysis is based on quarterly private non-farm inventory data from 1967Q1 to 2012Q, published by the Bureau of Economic Analysis. Results are based on *aggregate* data and on *disaggregated* data for the following five sectors: durable goods manufacturing, non-durable goods manufacturing, durable goods wholesale, non-durable goods wholesale, and

[11] If X_{t-1} includes unfinished goods, then the efficiency measure could capture more than just frictions in the goods market. In particular, it could also include efficiencies in the production process.

retail. Sales data for the aggregate series are *final* sales, either final total sales by domestic businesses or final sales of goods and structures. Sales data for the disaggregated series are *gross* series. The series based on the gross sales series possibly provide an inflated view of the efficiency of the sector as a whole, since gross sales include sales to other firms within the same sector.

The data are detrended using the Hodrick-Prescott (HP) filter in order to characterize data properties at business cycle frequencies. To study the possibility that data properties are different at high frequencies, band-pass filters are used to extract the fluctuations that are associated with cycles that have a period of less than one year and with cycles that have a period of less than two years.[12]

Tables 1 and 2 provide summary statistics for the series based on aggregate and disaggregated data, respectively. The two tables confirm some well-known facts about inventory behavior.[13] In particular, inventories and sales are positively correlated at business cycle frequencies. At higher frequencies, however, there is a negative correlation between sales and inventories for both series based on final sales.[14] For the series based on the gross sales measures, the correlation clearly drops if the frequency considered increases, but only four of the ten correlation coefficients turn negative.

Sales are also positively correlated with the investment in inventories.[15] That is, inventories tend to increase during periods when the cyclical component of sales is positive. This property is closely related to another well-known property, namely that output is more volatile than sales.[16] For the measures based on final sales, output is roughly ten

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[12] The detrended value of an observation is obtained using a band-pass filter that uses the observation itself and 12 lagging and 12 leading observations.

[13] See Ramey and West (1999) and McMahon (2011).

[14] Similar results are reported in Wen (2005).

[15] Since inventory investment can take on negative values, it is not possible to take logarithms to obtain a scale-free variable. The following is done to construct the cyclical component of inventory investment. First, inventory investment is divided by the trend value of GDP. Second, the HP-filter is applied to this ratio.

[16] Since output equals sales plus investment in inventories, output is necessarily more volatile than sales if sales and investment in inventories are postively correlated. Here, statistics are calculated for the logarithms of the variables. Consequently, the simple additive relationship no longer holds as an identity,

percent more volatile. For the measures based on gross sales, the difference is substantially smaller, but output is never less volatile than sales. This well-known ordering of volatilities has challenged the literature to come up with innovative inventory theories, since the traditional assumption of increasing marginal costs implies that firms would like to smooth production by using inventories as a buffer to absorb sales shocks.[17]

Next, consider the statistics related to the goods-market efficiency. The mean values of the goods-market efficiency for the two measures based on final sales are equal to 40% and 55%. Using the series based on gross sales, the mean efficiency measures are (not surprisingly) substantially higher and vary between 62% for wholesale durables and 79% for wholesale non-durables.

Figure 1 plots the cyclical component of GDP (top panel), the goods-market efficiency based on final sales of goods and structures (middle panel), and the goods-market efficiency for the manufacturing sector producing durable goods. To better understand the importance of the cyclical changes, the means of the goods-market efficiency measures are added to the cyclical components. The figure documents that the efficiency measures are clearly procyclical. Since goods-market efficiency is a monotone inverse function of the inventory-sales ratio, this is just another way to state the well-known fact that the inventory-sales ratio is countercyclical.[18] The correlations between goods-market efficiency and GDP are equal to 0.61 and 0.75 for the final sales and the durable manufacturing gross sales measure, respectively. The magnitudes of the cyclical fluctuations are nontrivial. The cyclical component of the goods-market efficiency for the durable manufacturing sector varies from a minimum of 59.0% to a maximum of 65.8%. Relative to the inventory-sales ratio, an advantage of the goods-market efficiency measure is that it is easier to interpret the magnitude of its cyclical fluctuations and to understand how important observed cyclical fluctuations potentially are for, for example, firm profitability. In particular, the observed difference between the just reported minimum and maximum values would correspond to

but the logic caries over to the analysis using logarithms.

[17] See Blinder and Maccini (1991), Ramey and West (1999), and McMahon (2011) for a detailed discussion.

[18] Bils and Kahn (2000) document the countercyclical behavior of the inventory-sales ratio.

a 12% drop in the sales price if firms would not be able to sell unsold goods in subsequent periods.[19] If one compares this with, for example, the usual magnitude of fluctuations in aggregate TFP, then these are numbers that cannot be ignored.[20]

Table 2 documents that the results are similar for several of the series based on sectoral gross sales, but not for all. In particular, the goods-market efficiency measures are procyclical for the durable and non-durable goods manufacturing sector, for the durable goods wholesale sector, but they are acyclical for the non-durable wholesale sector and the retail sector. The question arises whether the comovement between real activity and the goods-market efficiency in these two sectors remains low if a real activity measure for the sector itself would be used instead of GDP. Using equation (2), one can construct production measures that are consistent with the sales and inventory data used.[21] Using this real activity measure instead of GDP, the correlation coefficients for the non-durable goods wholesale and the retail sector, are substantially higher, namely 36% and 35%, respectively. This is still lower, however, than the corresponding numbers for the other sectors.

2.3 Tracking goods-market efficiency over the business cycle

To shed more light on the cyclical properties of goods-market efficiency, the following projection is calculated

$$\widehat{\pi}_{y,t} = \zeta_y \widehat{Y}_t + \zeta_x \widehat{X}_{t-1} + u_t, \tag{4}$$

where the circumflex indicates that the series have been detrended. As in Diamond (1982), a positive value for ζ_Y captures the idea that finding a suitable trading partner is easier in larger markets. Basic national income accounting tells us that goods produced this period will lead to income such as wages and profits. Therefore, $\widehat{Y}_t$ will affect both the

[19] Consequences for firm profits are less dramatic if inventories can be carried into the next period. However, inventory carrying costs are non-trivial. Richardson (1995) argues that inventory carrying costs are between 25% and 55% of the stock of inventories. Also see footnote 34.

[20] Recall that the standard deviation of aggregate TFP is typically assumed to be 0.7 per cent.

[21] For these calculations, the depreciation of inventories is set equal to ten percent, but the results are robust to changes in the depreciation rate used.

supply side and the demand side of the goods market. Beginning-of-period inventories, $\widehat{X}_{t-1}$ has less of an effect on this period's demand side, since it was produced in the past and typically generated income for workers and others when it was produced. If existing inventories mainly affect the supply side, then ζ_x would be negative. Even if demand is elastic then an increase in inventories could reduce would goods-market efficiency decrease if goods are competing for shelve space and/or sales staff.

Data are detrended either with the HP filter or with a third-order deterministic trend. Table 3 documents that the estimates for ζ_y are positive and those for ζ_x are negative.[22] Figures 2 and 3 plot goods-market efficiency measures, together with projections on key variables, when data are detrended using the HP filter and a deterministic trend, respectively. The dotted lines are the projection of the goods-market efficiency measure on just the cyclical GDP component. The dashed line is the projection on both cyclical GDP and cyclical inventories. The cyclical component of GDP clearly tracks key changes in the goods-market efficiency measures. As documented by these figures and the R-squares of table 3, the fit improves substantially if the cyclical component of inventories is included in the basis of the projection. Regarding the magnitudes, the largest coefficients for ζ_y are found for the durable goods manufacturing sector for which a 1% increase in the cyclical component of GDP corresponds to a 0.60 percentage point increase in the goods-market efficiency. The smallest effect is found for the non-durable wholesale sector for which the coefficient is only 0.06.

The explanatory variables are endogenous variables.[23] Thus, these are just projections and the coefficients do not necessarily capture the causal effect of a right-hand side variable on the dependent variable. Nevertheless, the results do hint at the possibility that the process of getting goods in the hands of the consumer becomes easier when aggregate real activity increases and becomes more difficult (per unit of available good for sale) when firms have more goods in inventories. Independent evidence for the estimates found here is given in section 5 in which it is shown that the theoretical model needs a positive value

[22]Tables 1 and 2 document that the same is true for the unconditional correlation of $\pi_{y,t}$ and the two right-hand side variables.

[23]When the HP filter is used, the right-hand side variables are not even be predetermined.

for ζ_y *and* a negative value for ζ_x to match observed inventory facts.

When inventories are added to the projection base, the projected values capture the severity of the fall in the goods-market efficiency during downturns much better. This may be surprising, since inventories are procyclical and the projection coefficient for inventories is negative. This would suggest that the fitted value of $\widehat{\pi}_{y,t}$ should decrease by *less* when inventories are added to the projection. The reason this does not always happen is the following. Cyclical fluctuations in inventories are larger than cyclical fluctuations in GDP. Moreover, it takes time to build down the large increase in the cyclical component of inventories that is formed during a boom. Consequently, the cyclical component of inventories can still be positive when the cyclical component of GDP is already negative. During such episodes both the negative cyclical component of GDP and the (still) positive cyclical component of inventories push the value of the goods-market efficiency down. This is exactly what happened during some of the deep recessions in the sample and can explain the improved fit during severe downturns when lagged inventories are included in the projection equation.

There are some low-frequency movements in the goods-market efficiency measures, but they do not always display a clear upward trend as one might expect given the improvements in inventory management. The strongest upward trend is observed for wholesale durables for which the efficiency measure is around 62% in the beginning of the sample and around 68% at the end of the sample.

2.4 Inventory accumulation during the recent recession

Although, inventories are procyclical at business cycle frequencies, they are countercyclical at higher frequencies as pointed out by Wen (2005) and confirmed here. The latter result is consistent with an increase in inventories at the onset of a recession. This is confirmed by Figure 4, which plots the cyclical components of GDP and inventories. The figure clearly shows the positive correlation of inventories and GDP, but the figure also documents that the cyclical component of inventories lags output and frequently continues to decrease (increase) when the cyclical component of GDP has already passed its turning point and is increasing (decreasing). During the recent recession, aggregate inventories also lag GDP, but the lag seems to be not more than one quarter.

The behavior of the aggregate series hide quite divergent behavior for the components. For example, from 2007Q3 to 2008Q2 (2008Q3), inventories of the durables-goods wholesale-trade sector increased by 4.2% (3.2%) compared with a drop in GDP of 1.1% (3.3%). Even larger increases are observed when inventories of particular subsectors are considered. Inventories of the "motor vehicles parts and supplies merchant" wholesale industry increased by 8% (11%) from 2007Q3 to 2008Q2 (2008Q3). Interestingly, the inventories of this sector display massive drops in subsequent quarters.[24] Inventories of the computers and software merchant wholesale industry increased by 10% (4%) from 2007Q3 to 2008Q2 (2008Q3). In contrast, these inventories did not display sharp drops in subsequent quarters. The largest increase in inventories is observed in the petroleum and coal product manufacturing industry. Inventories in this sector increased by 23% from 2007Q3 to 2008Q1.

3 Model

There are three types of agents in the economy. The first is a representative household that receives the earnings from its members and determines how much of aggregate income to consume and how much to invest in capital. This representative household consists of a continuum of entrepreneurs and a continuum of workers. This section describes the choice problems of the three different agents, the characteristics of the labor and the goods market, wage setting, and the equilibrium conditions.

Notation and reason for the endowment good. Aggregate variables, such as market prices and choices made by the representative household, are denoted by uppercase characters. Variables associated with choices of the individual firms are denoted by lowercase characters. Prices are expressed in terms of an endowment good. This good plays no

[24] The American Recovery and Reinvestment Act of 2009 is likely to have played a role, but inventories started to drop before the act was signed into law on February 17 2009.

role in the model at all, but is helpful to describe price and wage setting. In particular, it makes it clear that the price of the market-produced consumption good is fully flexible and adjusts to clear the goods market. By focusing on the case with flexible prices, it becomes clear that there is an interaction between frictions in the goods market and frictions in the labor market *even* when prices and wages are flexible. All variables that are expressed in units of the endowment good are denoted by a symbol with a circumflex. At the end of this section it is shown that the model equations can be rewritten to a system of equations in which the endowment good does not appear.

Household. A representative household chooses the consumption of the market-produced good, C_t, the consumption of the endowment good, $C_{e,t}$, and the amount of capital to carry over into the next period, K_t. For stock variables, such as K_t, the subscript t means that it is determined in period t, and available for production in period $t+1$.

The household consists of a continuum of workers that supply labor inelastically. The total mass of workers is given by Υ_N and the mass of employed workers is equal to N_t. The representative household receives income from employment, $\widehat{W}_t N_{t-1}$, income from renting out capital, $\widehat{R}_t K_{t-1}$, and income from firm ownership, $\widehat{D}_t$.

The maximization problem of the representative household is given by

$$\boldsymbol{V}(\boldsymbol{S}_t) = \max_{C_t, C_{e,t}, I_t, K_t} \frac{C_t^{1-\nu} - 1}{1-\nu} + U(C_{e,t}) + \beta \mathrm{E}_t \left[\boldsymbol{V}(\boldsymbol{S}_{t+1}) \right]$$

s.t.

$$\widehat{P}_t C_t + \widehat{P}_t I_t + C_{e,t} = \underline{C}_e + \widehat{R}_t K_{t-1} + \widehat{W}_t N_{t-1} + \widehat{D}_t, \tag{5}$$

$$I_t = K_t - (1 - \delta_k) K_{t-1}, \tag{6}$$

where I_t is investment, $\underline{C}_e$ is the quantity of the endowment good received, and $\boldsymbol{S}_t$ is the set of state variables.[25]

The first-order conditions are given by

$$\Lambda_{e,t} = \frac{\partial U(C_{e,t})}{\partial C_{e,t}}, \tag{7}$$

[25] The (not frequently used) symbols for the value function and the set of state variables are in bold and should be distinguished from the symbols for sales, S_t, and vacancies, V_t, which are not bold characters.

$$\widehat{P}_t \Lambda_{e,t} = C_t^{-\nu}, \tag{8}$$

$$\widehat{P}_t \Lambda_{e,t} = \beta \mathrm{E}_t \left[\Lambda_{e,t+1} \left(\widehat{R}_{K,t+1} + \widehat{P}_{t+1} \left(1 - \delta_k\right) \right) \right]. \tag{9}$$

As explained below, transactions in the goods market are characterized by a friction. However, the friction only affects the ability of the firm to find a trading partner; consumers can buy whatever they want without incurring any disutility or any other type of cost except having to pay for the goods acquired. Consequently, the household problem is characterized by the standard set of equations.[26]

Existing firms/jobs. A firm consists of one entrepreneur and one worker. The firm hires capital to produce output. The Bellman equation of the entrepreneur's problem is given by

$$\widehat{\boldsymbol{v}}(x_{t-1}; \boldsymbol{S}_t) = \max_{y_t, k_t, x_t} \left(\begin{array}{c} \left(\pi_{y,t} \left(y_t + x_{t-1} \right) \widehat{P}_t - \widehat{R}_t k_t - \widehat{W}_t \right) \\ + \beta \left(1 - \delta_n\right) \mathrm{E}_t \left[\Omega_{t+1} \widehat{\boldsymbol{v}}(x_t; \mathbf{S}_{t+1}) \right] \end{array} \right)$$

s.t.

$$y_t = \alpha_0 \exp\left(Z_t\right) k_t^{\alpha}, \tag{10}$$

$$x_t = \left(1 - \delta_x\right) \left(1 - \pi_{y,t}\right) \left(y_t + x_{t-1}\right), \tag{11}$$

where Ω_{t+1} is the marginal rate of substitution between one unit of wealth this period and one unit of wealth the next period. That is,

$$\Omega_{e,t+1} = \frac{\Lambda_{e,t+1}}{\Lambda_{e,t}} = \left(\frac{C_{t+1}}{C_t} \right)^{-\nu} \frac{\widehat{P}_t}{\widehat{P}_{t+1}}. \tag{12}$$

Moreover, δ_n denotes the probability of exogenous firm exit.[27] Z_t is an exogenous random variable affecting productivity and its law of motion is given by

$$Z_t = \rho_z Z_{t-1} + \varepsilon_t \text{ with } \varepsilon_t \sim N\left(0, \sigma_z^2\right).$$

[26] If the household chooses negative *gross* investment, then equation (5) implies that capital goods are transformed into goods that are immediately available for consumption without any cost or friction. This is a bit strange, since firms do face frictions when selling goods to consumers. These assumptions are harmless, however, since gross investment turns out to be always positive.

[27] δ_n is also the worker separation rate, since each firm consists of one worker.

The amount of products available for sale consists of newly produced output, y_t, and inventories available at the beginning of the period t, x_{t-1}. The probability to sell a good is equal to $\pi_{y,t}$. Thus, the quantity of unsold products is equal to $(1-\pi_{y,t})(\alpha_0 \exp(Z_t) k_{t-1}^{\alpha} + x_{t-1})$ of which a fraction $(1-\delta_x)$ is carried over as inventories into the next period. The parameter δ_x captures both physical depreciation as well as loss in value for other reasons.

The following first-order conditions characterize the solution of the entrepreneur's choice problem:

$$\widehat{R}_t = \left(\pi_{y,t}\widehat{P}_t + (1-\pi_{y,t})(1-\delta_x)\widehat{\lambda}_{x,t}\right)\alpha A \exp(Z_t) k_t^{\alpha-1}, \tag{13}$$

$$\widehat{\lambda}_{x,t} = (1-\delta_n)\beta \mathrm{E}_t\left[\Omega_{e,t+1}\frac{\partial \widehat{\boldsymbol{v}}(x_t;\mathbf{S}_{t+1})}{\partial x_t}\right]. \tag{14}$$

Here $\widehat{\lambda}_{x,t}$ is the value of relaxing the constraint given in equation (11). It represents the value of leaving period t with one more unit of inventories (after depreciation). The value of a unit of inventories at the beginning of the period is given by

$$\widehat{\boldsymbol{v}}_{x,t} = \frac{\partial \widehat{\boldsymbol{v}}(x_{t-1};\mathbf{S}_t)}{\partial x_{t-1}} = \left(\begin{array}{c} \pi_{y,t}\widehat{P}_t \\ +(1-\pi_{y,t})(1-\delta_x)\widehat{\lambda}_{x,t}\end{array}\right). \tag{15}$$

Using this equation, first-order condition (14) can be written as

$$\widehat{\lambda}_{x,t} = (1-\delta_n)\beta \mathrm{E}_t\left[\Omega_{e,t+1}\left(\begin{array}{c} \pi_{y,t+1}\widehat{P}_{t+1} \\ +(1-\pi_{y,t+1})(1-\delta_x)\widehat{\lambda}_{x,t+1}\end{array}\right)\right]. \tag{16}$$

Choosing to accumulate additional inventory. In this model, firms passively accumulate inventories. The question arises whether it could be optimal to accumulate *additional* inventories. That is, could it ever be optimal to keep some goods in storage instead of trying to sell them? The answer is no. If a firm puts a unit of goods on the market, then the expected payoff is equal to $\pi_{y,t}\widehat{P}_t + (1-\pi_{y,t})(1-\delta_x)\widehat{\lambda}_{x,t}$. If it chooses to keep the unit in inventories, then the expected payoff is equal to $(1-\delta_x)\widehat{\lambda}_{x,t}$. It would only do the latter if

$$\widehat{\lambda}_{x,t} > \frac{\widehat{P}_t}{1-\delta_x} \tag{17}$$

Thus, a firm would *choose* to put a good into inventories if the value of doing so is sufficiently above the market value of a market-produced good this period. This never happens.[28]

Firm heterogeneity and firm value. A newly created firm starts with zero inventories. As time goes by, the firm will accumulate inventories. Firms only differ in the amount of inventories they hold. Moreover, the only aspect of the distribution of inventories that is relevant for agents' decisions and the behavior of aggregate variables is the *aggregate* level of inventories. Key for this result is the assumption that $\pi_{y,t}$ does not depend on the *firm's* level of inventories.[29] This assumption implies that $\boldsymbol{v}_{x,t}$ does not depend on the level of x_{t-1}. Consequently,

$$\widehat{\boldsymbol{v}}\left(x_{t-1};\boldsymbol{S}_t\right)=\widehat{\boldsymbol{v}}\left(0;\boldsymbol{S}_t\right)+x_{t-1}\widehat{\boldsymbol{v}}_{x,t}. \tag{19}$$

That is, the value of each firm consists of two parts. The first part is the value of the firm *without* inventories, $\widehat{\boldsymbol{v}}\left(0;\boldsymbol{S}_t\right)$. The second part is the value of the stock of inventories, $x_{t-1}\widehat{\boldsymbol{v}}_{x,t}$. Reallocations of inventories across firms have no aggregate consequences, since $\widehat{\boldsymbol{v}}_{x,t}$ does not depend on the level of x_t.

The value of a firm with no inventories is given by

$$\begin{aligned}\widehat{\boldsymbol{v}}\left(0;\boldsymbol{S}_t\right) &= \left(\begin{array}{c}\pi_{y,t}\widehat{P}_t\alpha_0\exp\left(Z_t\right)k_t^{\alpha}-\widehat{R}_tk_t-\widehat{W}_t\\ +\left(1-\delta_n\right)\beta\mathrm{E}_t\left[\Omega_{t+1}\widehat{\boldsymbol{v}}(\left(1-\pi_{y,t}\right)\left(1-\delta_x\right)\alpha_0\exp\left(Z_t\right)k_t^{\alpha};\boldsymbol{S}_{t+1})\right]\end{array}\right) \\ &= \left(\begin{array}{c}\pi_{y,t}P_t\alpha_0\exp\left(Z_t\right)k_t^{\alpha}-\widehat{R}_tk_t-\widehat{W}_t\\ +\left(1-\delta_n\right)\beta\mathrm{E}_t\left[\Omega_{t+1}\left(\begin{array}{c}\widehat{\boldsymbol{v}}(0;\boldsymbol{S}_{t+1})\\ +\left(1-\pi_{y,t}\right)\left(1-\delta_x\right)\alpha_0\exp\left(Z_t\right)k_t^{\alpha}\widehat{\boldsymbol{v}}_{x,t+1}\end{array}\right)\right]\end{array}\right).\end{aligned} \tag{20}$$

where k_t is the optimal choice for capital.

[28] To understand why this is the case, suppose that there is no uncertainty. If $\widehat{\lambda}_{x,t}/\widehat{P}_t>\left(1-\delta_x\right)^{-1}$, then equations (9) and (16) imply that

$$\frac{\left(1-\delta_n\right)}{\left(\widehat{R}_{t+1}/\widehat{P}_{t+1}+\left(1-\delta_k\right)\right)}\left[\pi_{y,t+1}+\left(1-\pi_{y,t+1}\right)\left(1-\delta_x\right)\frac{\widehat{\lambda}_{x,t+1}}{\widehat{P}_{t+1}}\right]=\frac{\widehat{\lambda}_{x,t}}{\widehat{P}_t}>\frac{1}{1-\delta_x}, \tag{18}$$

which implies that $\lambda_{x,t+1}/\widehat{P}_{t+1}$ is also bigger than $\left(1-\delta_x\right)^{-1}$ unless the net return on capital $\widehat{R}_{K,t+1}/\widehat{P}_{t+1}-\delta_K$ is sufficiently negative. Such speculative events do not occur in this model.

[29] Consistent with the empirical results, $\pi_{y,t}$ is allowed to depend on beginning-of-period *aggregate* inventories. This property does not affect the aggregation result discussed here.

Using equation (15), the last equation can be written as

$$\widehat{\boldsymbol{v}}(0;\boldsymbol{S}_t)=\left(\begin{array}{c}\left(\begin{array}{c}(\pi_{y,t}\widehat{P}_t+(1-\pi_{y,t})(1-\delta_x)\widehat{\lambda}_{x,t})\alpha_0\exp(Z_t)\,k_t^{\alpha}\\ -\widehat{R}_tk_t-\widehat{W}_t\end{array}\right)\\ +(1-\delta_n)\,\beta\mathrm{E}_t\left[\Omega_{t+1}\widehat{\boldsymbol{v}}(0;\boldsymbol{S}_{t+1})\right]\end{array}\right). \tag{21}$$

Labor market and labor market friction. Job creation requires an entrepreneur starting a project and finding a worker. The per-period cost of this joint activity is equal to ψ units of the market good. The assumption of free entry implies that in equilibrium the cost of creating a job equals the expected benefit. This means that

$$\psi\widehat{P}_t\Lambda_{e,t}=\pi_{f,t}\beta\mathrm{E}_t\left[\Lambda_{e,t+1}\widehat{\boldsymbol{v}}\left(0;\mathbf{S}_{t+1}\right)\right], \tag{22}$$

where $\pi_{f,t}$ is the number of matches per vacancy.

The total number of jobs created, N_t^{new}, depends on the number of vacancies posted, V_t, and the number of unemployed workers (Υ_N-N_{t-1}). The matching technology is characterized by a Cobb-Douglas production function, thus[30]

$$N_t^{\text{new}} = \phi_0V_t^{\phi_1}\left(\Upsilon_N-N_{t-1}\right)^{1-\phi_1}, \tag{23}$$

$$N_t = (1-\delta_n)\,N_{t-1}+N_t^{\text{new}}, \text{ and} \tag{24}$$

$$\pi_{f,t} = \phi_0\left(\frac{\Upsilon_N-N_{t-1}}{V_t}\right)^{1-\phi_1}. \tag{25}$$

Total investment in job creation is equal to ψV_t.

Goods market and the goods-market friction. In the description above, firms do not always sell their products. This is motivated with a very simple matching friction according to which the firm does not find a buyer for every product it puts up for sale. If the standard approach would be used, then the amount of goods available *as well as* the

[30] We allow for the possibility that $N_t^{\text{new}}>V_t$, that is, the number of matches could exceed the number of vacancies. In simulated data this does happen, but not very often. If it happens, then firms end up with more than one worker per vacancy. This is not problematic as long as $\pi_{f,t}$ is not interpreted as a probability. Imposing that $N_t^{\text{new}}\leq V_t$ makes it more difficult to solve the model accurately. The case in which $N_t^{\text{new}}>(\Upsilon_N-N_{t-1})$ did not occur.

search effort by consumers would affect total sales. It obviously makes sense to assume that consumers have to put in some effort to buy products, which for some consumers is an enjoyable activity and for some it is not. It is less clear, however, whether *changes* in the amount of effort that consumers put into the activity of acquiring goods are important for cyclical fluctuations in the number of goods firms sell when one controls for changes in demand for the good itself. Such changes do play a role in Petrosky-Nadeau and Wasmer (2011), Bai, Ríos-Rull, and Storesletten (2012), and Michaillat and Saez (2013). In the models of these papers, recessions are deeper because shopping itself requires effort?[31] That may be the case, but the search friction adopted here does not rely on changes in the search effort of consumers. Here it is assumed that variations in search effort over and above a minimum level are *not* important for the actual number of transactions and the following formulation is used:[32]

$$S_t = \pi_{y,t} \left(N_{t-1} y_t + X_{t-1} \right), \tag{26}$$

and $\pi_{y,t}$ is given by

$$\pi_{y,t} = \underline{\pi}_y + \zeta_y \left(Y_t - \underline{Y} \right) + \zeta_x \left(X_{t-1} - \underline{X} \right), \tag{27}$$

[31] In fact, one could argue that unemployed workers have more time to shop, which would imply that search frictions in the goods market are *less* severe during recessions, since more consumers are unemployed during recessions and, thus, have more time to shop. Indeed, Kaplan and Menzio (2013) assume that unemployed consumers can visit more stores.

[32] This formulation implicitly imposes that customers do put in the minimum level required so that sales are not zero. A more complete specification would be the following:

$$S_t = \begin{cases} \pi_{y,t} \left(N_{t-1} y_t + X_{t-1} \right)^{\nu_1} \underline{E}^{\nu_2} & \text{if } E_t \geq \underline{E} \\ 0 & \text{if } E_t < \underline{E} \end{cases} \quad 0 < \nu_1, \nu_2 \leq 1,$$

where E_t denotes the effort level and $\underline{E}$ denotes the minimum effort level, e.g., the cost of going to the market place. If an increase in E_t reduces utility, then $E_t = \underline{E}$. The assumption is made that the disutility of putting in $\underline{E}$ is low enough, so that E_t is always equal to $\underline{E}$. We also assume that $\nu_1 = 1$. For the results in this paper, the value of ν_1 does not matter, since a process for $\pi_{y,t}$ is chosen such that goods-market efficiency, i.e., the level of sales, S_t, relative to the amount of available goods, $N_{t-1}y_t + X_{t-1}$, mimics the cyclicality of its empirical counterpart. The lower ν_1, the more procyclical $\pi_{y,t}$ has to be to make goods-market efficiency procyclical, that is, the calibrated value of ζ_y would be higher.

where a bar under a symbol indicates that it is the variable's steady state value, $\zeta_y \geq 0$, and $\zeta_x \leq 0$. A positive dependence of $\pi_{y,t}$ on the size of the market, Y_t, is similar to the search externality in the pathbreaking analysis in Diamond (1982). Moreover, a positive value for ζ_y is consistent with the empirical findings based on aggregate data of section 2.3 and the empirical findings based on commercial aircraft markets of Gavazza (2011). The empirical analysis of this paper indicates a negative dependence of $\pi_{y,t}$ on beginning-of-period aggregate inventories. It does not seem unreasonable, that a higher stock of inventories reduces the chance of selling a given good. This raises the question why it also would not be more difficult to sell goods when the amount of *newly* produced goods, Y_t, increases. However, there is an important difference between a higher GDP, Y_t, and a higher level of aggregate inventories, X_{t-1}. A higher level of GDP not only means that the supply of goods increases, it also means that demand increases, since income earned is higher. In contrast, a higher level of beginning-of-period aggregate inventories definitely means that the supply of goods is higher, but will in general not lead to an equal increase in income.[33]

Wages. Instead of specifying a bargaining processes for wages, I adopt a flexible approach to model the behavior of the wage variable that matters, i.e., the real wage rate. In particular, the wage rate rule is given by

$$\frac{\widehat{W}_t}{\widehat{P}_t} = \omega_0 \left(\begin{array}{c} \omega_1 \frac{\left(\left(\pi_{y,t}\widehat{P}_t + (1-\pi_{y,t})(1-\delta_x)\widehat{\lambda}_{x,t}\right)\alpha_0 k_t^{\alpha} - \widehat{R}_t k_t\right)}{\widehat{P}_t} \\ +(1-\omega_1)\frac{\left(\left(\underline{\pi}_y \underline{\widehat{P}} + (1-\underline{\pi}_y)(1-\delta_x)\underline{\widehat{\lambda}}_x\right)\alpha_0 \underline{k}^{\alpha} - \underline{\widehat{R}}\,\underline{k}\right)}{\underline{\widehat{P}}} \end{array} \right), \tag{28}$$

where a lower bar indicates the steady state value, $0 \leq \omega_1 \leq 1$, and $0 < \omega_0 < 1$. Note that all variables in the wage rate rule are expressed in units of the market-produced good, not the endowment good. The two terms on the right-hand side are the level of current-period revenues net of rental costs with unsold goods valued at $(1-\delta_x)\widehat{\lambda}_{x,t}$ and its steady state

[33] Inventories are produced in the past. Workers that produced these inventories were paid in the past. Depending on how inventories are valued, the production of inventories may even have generated income through profits. The actual sale of inventories may generate *additional* income in the current period when the sale price exceeds the accounting price used to value inventories, but the value of this additional income is likely to be less than the total value of the inventories available for sale.

equivalent. If $\omega_1 = 0$, then the real wage rate is fixed. If $\omega_1 > 0$, then wages increase with the firm's net revenues. ω_0 indicates the average share of revenues net of rental costs that goes to the worker. The other fraction goes to the entrepreneur as compensation for creating the job.

Inventories when prices are flexible. It is assumed that prices in the goods market are such that the consumer is indifferent between buying and not buying an additional unit. That is,

$$\widehat{P}_t \frac{\partial U(C_{e,t})}{\partial C_{e,t}} = C_t^{-\nu}. \tag{29}$$

The price level is flexible. This raises the question why the price level does not adjust to ensure that all products are sold. The reason is the following. Ex ante, i.e., before trading starts, all firms are the same. Thus, it makes sense to focus on the case in which all firms charge the same price. In equilibrium, prices are such that the implied amount that customers demand, S_t, and the implied amount that firms supply, Q_t, is such that

$$S_t = \pi_{y,t} Q_t, \text{ where} \tag{30}$$

$$Q_t = N_{t-1}\alpha_0 \exp(Z_t) k_t^{\alpha} + X_{t-1}. \tag{31}$$

When choosing the amount of goods supplied, Q_t, firms take into account that only a fraction $\pi_{y,t}$ is sold. Ex post, some goods are sold and some are not. If a firm did not sell some products, then it has an incentive to lower the price of these unsold goods *if* the goods can still be sold within the same period. This possibility is ruled out by assumption. That is, firms only find out at the end of the period whether a good is sold or not. At that point, the next period starts. At the beginning of this next period, a good that is newly produced is not distinguishable from a good that was produced in the past and did not sell (adjusted for any possible depreciation). Consequently there is no reason why the firm offering goods out of inventories should charge lower prices.

Aggregation and equilibrium. Individual firms have different levels of inventories. For example, newly created firms have no inventories at all. But it is easy to obtain an expression for aggregate inventories. All firms face the same value for $\pi_{y,t}$, which implies that all firms choose the same level for capital, i.e., $k_{i,t} = k_t$. The law of motion for aggregate inventories, X_t, is thus equal to

$$\begin{aligned} X_t &= (1-\delta_n)(1-\delta_x)\sum_i \left[(1-\pi_{y,t})\left(\alpha_0 \exp(Z_t) k_t^{\alpha}\right) + x_{i,t-1}\right] \\ &= (1-\delta_n)(1-\delta_x)\left[N_{t-1}(1-\pi_{y,t})\alpha_0 \exp(Z_t) k_t^{\alpha}\right] + (1-\pi_{y,t}) X_{t-1} \\ &= (1-\delta_n)(1-\delta_x)(1-\pi_{y,t})\left(\alpha_0 \exp(Z_t) K_{t-1}^{\alpha} N_{t-1}^{1-\alpha} + X_{t-1}\right). \end{aligned}$$

Equilibrium in the rental market for capital goods requires that

$$N_{t-1} k_t = K_{t-1}, \tag{32}$$

that is, the amount of capital firms choose in period t, k_t, is equal to the available amount of capital per firm. Total amount of cash flows generated in the corporate sector, $\widehat{D}_t$, is given by

$$\widehat{D}_t = \pi_{y,t}\widehat{P}_t\left(N_{t-1}\alpha_0 \exp(Z_t) k_t^{\alpha} + X_{t-1}\right) - \widehat{W}_t N_{t-1} - \widehat{R}_t K_{t-1} - \psi V_t. \tag{33}$$

An equilibrium is a set of functions $\pi_y(\boldsymbol{S}_t)$, $\pi_f(\boldsymbol{S}_t)$, $\widehat{P}(\boldsymbol{S}_t)$, and $\widehat{W}(\boldsymbol{S}_t)$ and a set of policy functions for the agents' choices such that (i) the policy functions solve the corresponding optimization problems taking probabilities and prices as given and (ii) and the policy functions imply $\pi_y(\boldsymbol{S}_t)$, $\pi_f(\boldsymbol{S}_t)$, $\widehat{P}(\boldsymbol{S}_t)$, and $\widehat{W}(\boldsymbol{S}_t)$.

Walras law. Goods market equilibrium requires that

$$C_t + I_t + \psi V_t = \pi_{y,t}\left(\alpha_0 \exp(Z_t) K_t^{\alpha} N_t^{1-\alpha} + X_{t-1}\right).$$

This equation is implied by the budget constraint of the household and the definition of $\widehat{D}_t$.

Simplified model equations. The price level of the market-produced consumption good, $\widehat{P}_t$, is allowed to vary freely. That is, the model does not rely on sticky prices. Real wages are determined by equation (28). This process will be calibrated such that the model generates a realistic amount of wage volatility. As long as the specification for wages is for real wages, the model can be represented by a set of equations in which the price of the market-produced consumption good is the numeraire and equal to 1 and the endowment good does not appear. This latter system is simpler, but when the price of the market-produced consumption good is the numeraire, it is less transparent that prices are allowed to vary with market conditions.

This simplified model is given by the following set of equations:

$$C_t + I_t + \psi V_t = \pi_{y,t}\left(\alpha_0 \exp\left(Z_t\right) K_t^{\alpha} N_t^{1-\alpha} + X_{t-1}\right), \tag{34}$$

$$I_t = K_t - \left(1-\delta_k\right) K_{t-1}, \tag{35}$$

$$\Lambda_t = C_t^{-\nu}, \tag{36}$$

$$\Lambda_t = \beta \mathrm{E}_t\left[\Lambda_{t+1}\left(R_{t+1} + \left(1-\delta_k\right)\right)\right], \tag{37}$$

$$\Omega_{t+1} = \frac{\Lambda_{t+1}}{\Lambda_t} = \left(\frac{C_{t+1}}{C_t}\right)^{-\nu}, \tag{38}$$

$$R_t = \left(\pi_{y,t} + \left(1-\pi_{y,t}\right)\left(1-\delta_x\right)\lambda_{x,t}\right)\alpha A \exp\left(Z_t\right) k_t^{\alpha-1}, \tag{39}$$

$$\lambda_{x,t} = \left(1-\delta_n\right)\beta \mathrm{E}_t\left[\Omega_{t+1}\begin{pmatrix} \pi_{y,t+1} \\ +\left(1-\pi_{y,t+1}\right)\left(1-\delta_x\right)\lambda_{x,t+1}\end{pmatrix}\right], \tag{40}$$

$$\boldsymbol{v}(0;\boldsymbol{S}_t) = \begin{pmatrix} \begin{pmatrix} \pi_{y,t} + \left(1-\pi_{y,t}\right)\left(1-\delta_x\right)\lambda_{x,t})\alpha_0 \exp\left(Z_t\right) k_t^{\alpha} \\ -R_t k_t - W_t \end{pmatrix} \\ +\left(1-\delta_n\right)\beta \mathrm{E}_t\left[\Omega_{t+1}\boldsymbol{v}(0;\boldsymbol{S}_{t+1})\right] \end{pmatrix}, \tag{41}$$

$$\psi = \pi_{f,t}\beta \mathrm{E}_t\left[\Omega_{t+1}\boldsymbol{v}\left(0;\mathbf{S}_{t+1}\right)\right], \tag{42}$$

$$N_t^{\text{new}} = \phi_0 V_t^{\phi_1}\left(\Upsilon_N - N_{t-1}\right)^{1-\phi_1}, \tag{43}$$

$$N_t = \left(1-\delta_n\right) N_{t-1} + N_t^{\text{new}}, \tag{44}$$

$$\pi_{f,t} = \phi_0\left(\frac{\Upsilon_N - N_{t-1}}{V_t}\right)^{1-\phi_1}, \tag{45}$$

$$\pi_{y,t} = \underline{\pi}_y + \zeta_y\left(Y_t - \underline{Y}\right) + \zeta_x\left(X_{t-1} - \underline{X}\right), \tag{46}$$

$$X_t = \left(1-\delta_n\right)\left(1-\pi_{y,t}\right)\left(1-\delta_x\right)\left(\left(\alpha_0 \exp\left(Z_t\right) K_{t-1}^{\alpha} N_{t-1}^{1-\alpha} + X_{t-1}\right), \tag{47}$$

$$W_t = \omega_0\begin{pmatrix} \omega_1\left((\pi_{y,t} + (1-\pi_{y,t})(1-\delta_x)\lambda_{x,t})\alpha_0 k_t^{\alpha} - R_t k_t\right) \\ +\left(1-\omega_1\right)\left(\left(\underline{\pi}_y + (1-\underline{\pi}_y)(1-\delta_x)\lambda_x\right)\alpha_0 \underline{k}^{\alpha} - \underline{R\,k}\right) \end{pmatrix}. \tag{48}$$

4 Calibration

The parameters β, α, δ_k and ν are set to standard values. In particular, $\beta = 0.99$, $\alpha = 0.3$, $\delta_k = 0.025$, and $\nu = 1$. Typical values for the parameters of the law of motion for productivity, ρ_z and σ_z, are 0.95 and 0.007. In addition, the results are given for a process with a value for ρ_z equal to 0.7 and a value for σ_z such that the volatility of Z_t is the same for the two processes. By considering a less persistent process for the stochastic driving variable, it becomes clear that the model can generate very persistent behavior even when Z_t itself is not that persistent. The depreciation rate of inventories, δ_x, is set equal to 0.10. This captures physical depreciation but also other possible reasons for value reduction and storage costs.[34]

The wage process is characterized by two parameters, ω_0 and ω_1. The value of ω_0 is chosen to match a measure of observed employment volatility, namely $\sigma(\ln N)/\sigma(\ln Y)$. The value of the target is equal to 0.466 which is also used in Den Haan and Kaltenbrunner (2009). This target for employment volatility is based on employment data from the Current Population Survey, which leads to a conservative estimate of employment volatility. Matching a higher level of employment volatility would imply a higher level of ω_0, that is, a lower average profit margin. When profit margins are lower, changes in goods-market efficiency would have even stronger effects on job creation. That is, choosing a conservative target for $\sigma(\ln N)/\sigma(\ln Y)$ limits the importance of changes in the goods-market efficiency. Following Den Haan and Kaltenbrunner (2009), ω_1 is set equal to 3/4, that is, wages respond quite strongly to current-period profits. Several empirical studies suggest that wages could very well be much less responsive. This is true for results based on estimated DSGE models and for results based on micro-level wage data.[35] Thus, the results

[34] The value of this parameter is conservative. It is slightly lower than the value used by Khan and Thomas (2007), who calculate the cost of inventory storage cost to be equal to 12% of the value of inventories held. Their calculations are based on data provided by Stock and Lambert (1987) and Richardson (1995). The estimates of the latter are substantially higher, because they include the cost of money, insurance, and taxes, which should not be part of δ_x in this model.

[35] See Barattieri, Basu, and Gottschalk (2010).

here do not rely on having sticky wages.[36]

The specification for goods-market efficiency depends on three parameters, $\underline{\pi}_y$, ζ_y, and ζ_x. The value of $\underline{\pi}_y$ is the steady state value of $\pi_{y,t}$ and is set equal 0.4, which is the average of the observed measure for goods-market efficiency for final sales of domestic businesses, as documented in table 1. As discussed below, the values of ζ_y and ζ_x are chosen to match a measure of the volatility of $\pi_{y,t}$, namely $\sigma(\pi_y)/\sigma(Y)$, and a measure of the volatility of sales, namely $\sigma(S)/\sigma(Y)$.

The remaining parameters are related to employment determination. Following the literature, ϕ_1 is set equal to 0.5, which means that the elasticity of $\pi_{f,t}$ with respect to labor market tightness is equal to one half.[37] Based on results in Den Haan, Ramey, and Watson (2000), the job destruction rate, δ_n, is set equal to 0.052 and the values for the scaling coefficient in the matching function, ϕ_0, and the cost of starting a project, ψ, are such that the steady state unemployment rate is equal to 12% and the steady state value for the number of matches per vacancy is equal to 0.71.[38] This measure for the unemployment rate takes into account those workers that indicate that they would like to work but are not counted in the formal unemployment definition.

5 Results

Two experiments are discussed to bring to light key properties of the model. In the first experiment, the ability to sell, $\pi_{y,t}$ only depends on aggregate output and not on beginning-of-period aggregate inventories. The parameter affecting the dependence of $\pi_{y,t}$ on aggregate output, ζ_y, is chosen such that the volatility and the procyclical behavior of goods-market efficiency, $\pi_{y,t}$, match their empirical counterparts. Another key parameter in this experiment is ω_0, the share of revenues that accrues to the workers. Hagedorn and Manovskii (2008) point out that the response of employment to changes in firm revenues

[36] In fact, the value of ω_1 is not important in this paper. The reason is that ω_0 is set to match observed employment volatility. If ω_1 is lowered, then a higher value of ω_0 would ensure that employment volatility would not be affected.

[37] Empirical support for this value is given in Petrongolo and Pissarides (2001).

[38] The latter is based on van Ours and Ridder (1992).

is larger when ω_0 is higher and the profit margin is, thus, lower. Therefore, changes in $\pi_{y,t}$ will have a larger impact on the economy if ω_0 is closer to 1. To discipline the model's response to changes in $\pi_{y,t}$, the value of ω_0 is chosen such that the model generates a realistic (but conservative) amount of employment volatility.[39]

In the second experiment, $\pi_{y,t}$ depends not only (positively) on aggregate activity, but—motivated by this paper's empirical findings—also depends negatively on the beginning-of-period aggregate level of inventories.

Finding the parameter values at which the model exactly hits the targets entails a non-trivial search in the parameter space. Moreover, the calibration procedure relies on second-order moments, the calculation of which requires a numerical solution of the policy functions. Consequently, a fast solution method is needed. The results reported are based on first-order perturbation. At the calibrated parameter values, the model is also solved with a global solution method and the results reported here are very similar for the two solution methods.

5.1 The role of a procyclical goods-market friction for business cycles

As documented in section 2, goods-market efficiency, $\pi_{y,t}$, is procyclical and quite volatile. The ability to sell, $\pi_{y,t}$, affects firm profitability and, thus, aggregate activity and it is in turn affected by the level of aggregate activity. Consequently, variation in $\pi_{y,t}$ could be an important channel through which shocks are magnified and propagated. In this subsection, the specification for $\pi_{y,t}$ is given by

$$\pi_{y,t} = \underline{\pi}_y + \zeta_y \left(Y_t - \underline{Y} \right). \tag{49}$$

That is, $\pi_{y,t}$ is allowed to depend on aggregate real activity, but not on aggregate inventories. Model properties are presented in table 4, which reports unconditional business cycle moments, and in figure 5, which displays the impulse response functions (IRFs).

[39]It is not straightforward to calibrate ω_0 using direct measures of entrepreneurial compensation. Observed profit shares include compensation for equity financing while in the model $1 - \omega_0$ is only the compensation for the entrepreneurial activity of creating a job.

The role of inventories for GDP fluctuations. First consider the benchmark results when ζ_y and ω_0 are chosen such that the model exactly matches the observed cyclical behavior of goods market efficiency and employment. Since goods-market efficiency is a simple transformation of the inventory-sales ratio, the calibration automatically ensures that the model also matches the cyclical behavior of the inventory-sales ratio. The table documents that the model predicts the typical ordering of the volatility of consumption, investment, and output. The calculated shares of investment in inventories for GDP fluctuations are equal to 0.149 and 0.094 when ρ is equal to 0.7 and 0.95, respectively. The empirical counterpart is equal to 0.193. Thus, a non-trivial part of GDP fluctuations is attributable to investment in inventories, although this version of the model somewhat underpredicts the importance of inventories for business cycle fluctuations of GDP.

At the calibrated parameter values, the IRFs of inventories and sales associated with a positive shock to Z_t are positive at all time horizons. With both responses being positive, it is not surprising that the model correctly predicts that inventories are positively correlated at business cycle frequencies. The model also correctly predicts that inventories and sales are *negatively* correlated at higher frequencies. This is more surprising given that the IRFs of both variables are positive. The reason is that the response of inventories is a bit delayed. This means that the high-frequency component of the inventories response is initially negative, whereas the high-frequency component of the real activity response is initially positive.

Magnification and persistence. The autocorrelation coefficients for employment and output indicate that the model is capable of adding quite a bit of persistence. For example, when $\rho = 0.7$, the autocorrelation coefficients are equal to 0.982 and 0.997 for employment and output, respectively.[40]

Figure 5 displays the IRFs of employment, output, and goods-market efficiency. To facilitate comparison, the IRF of productivity is also shown in the panels for the employment IRF and the output IRF. The variance of the innovation is chosen such that the unconditional variance of Z_t is the same for the two values of ρ. Consequently, the process

[40] Since filtering also affects the autocorrelation, the unfiltered series are used to calculate these statistics.

with the higher value for ρ has a smaller innovation variance and, thus, smaller initial responses. The IRFs are given for three different values of ζ_y. The first value is the one for which model predictions for $\pi_{y,t}$ match the observed cyclical behavior of its empirical counterpart. The second value of ζ_y considered is 0. A comparison of the responses when $\zeta_y = 0$ with the responses for the calibrated value of ζ_y reveals the role of goods-market friction in magnifying and propagating shocks. The third value of ζ_y is such that the model responses to the *non-permanent* shock considered are close to being permanent. By considering higher values of ζ_y one learns what the role of goods-market frictions can be if parameter choice is not or is less constrained by the observed volatility of $\pi_{y,t}$.

The graphs show that the employment and output responses to a shock to Z_t are substantially more persistent than the responses of Z_t itself. This is also true when $\zeta_y = 0$ and $\pi_{y,t}$ is, thus, constant. When ζ_y equals zero, shocks are propagated because of the matching friction and the desire to smooth consumption. The responses are more persistent, however, when ζ_y is equal to its calibrated value and substantially so when $\rho = 0.7$. The same is true for the magnification of the shock. When $\rho = 0.95$, that is, when the underlying shock is already quite persistent, then the model does not add a lot of magnification and additional persistence when ζ_y is equal to its calibrated value. When ζ_y is increased above its calibrated value, however, then the goods-market friction also generates remarkable magnification and propagation when $\rho = 0.95$.

Why this version cannot match all inventory and sales facts. At the calibrated parameter values, the model predicts that output and sales have roughly the same volatility. In the data, however, sales are *less* volatile than output. This somewhat surprising empirical finding has triggered an extensive literature with ingenious attempts to build models to get this right. The model developed here could generate the right ordering for the volatility of sales and output quite easily. As indicated in the "$\zeta_y = 0$" column in table 4, sales are substantially less volatile than output when goods-market efficiency is constant, especially when $\rho = 0.7$. When $\pi_{y,t}$ is constant, then sales are simply a fraction of the amount of available goods for sale, that is, newly produced goods *plus* the stock of inventories. The latter is a stock variable and less volatile than output. Consequently, when sales are a constant fraction of the sum of output and inventories, then sales will be less volatile than output.

The problem with setting ζ_y equal to zero and keeping $\pi_{y,,t}$ constant, however, is that the model would no longer generate the right cyclical behavior for the goods-market efficiency measure, $\pi_{y,t}$, and, thus, would not generate the right cyclical behavior of the inventory-sales ratio. Starting at zero, an increase in ζ_y induces volatility in the goods-market efficiency measure, which is consistent with the data. As long as ζ_y is low enough, the model also correctly predicts that sales are less volatile than output. However, when ζ_y is such that the model matches the volatility of $\pi_{y,t}$, the volatility of sales exceeds the volatility of output. Consequently, the model cannot match both the correct procyclical behavior of $\pi_{y,t}$ and the right relative volatility of sales and output by only changing ζ_y. In the next subsection, it will be shown that the model can match both properties by allowing $\pi_{y,t}$ to also depend on aggregate inventories.

The role of the goods-market friction. The finding that the model's implications become increasingly at odds with well-known facts from the inventory literature as ζ_y takes on higher values also means that the role of the goods-market friction for magnification and propagation is limited. This is most clear when $\rho = 0.95$. In this case, the value of ζ_y, that is, the importance of cyclical fluctuations in the goods-market friction, can be increased a lot before the model's solution becomes explosive. As documented in figure 5, the model generates stunning magnification and propagation at high values for ζ_y. Moreover, figure 5 also documents that $\pi_{y,t}$ drops just a few percentage points at the highest value for ζ_y considered. Although the implied volatility for $\pi_{y,t}$ is higher than what is observed in the data, the generated changes in $\pi_{y,t}$ do not seem outlandish. However, some implications for the model's properties regarding inventories are clearly inconsistent with the data when ζ_y takes on high values.

It is quite intuitive that making goods-market frictions more important will at some point imply that the model's predictions for sales and inventories deteriorates. Consider a negative TFP shock. The reduction in economic activity induces a reduction in $\pi_{y,t}$. The larger the value of ζ_y, the larger the reduction in $\pi_{y,t}$ and the stronger shocks are magnified and propagated. But the reduction in $\pi_{y,t}$ also implies that less is sold relative to what is produced. As the reduction in $\pi_{y,t}$ becomes larger, then at some point sales will drop by *more* than output and inventories will *in*crease. Both properties are inconsistent with observed facts. Again consider the case when $\rho = 0.95$ and ζ_y is set equal to its highest possible value. In this case, the standard deviation of sales is 1.823 time the standard deviation of output, whereas the empirical ratio is only 0.901. Similarly, the correlation between inventories and sales is *negative* whereas it is positive in the data.

5.2 Results when goods market friction also depends on inventories

The results discussed so far show that the model cannot simultaneously match the correct cyclical behavior of goods-market efficiency and predict that sales are less volatile than output when $\pi_{y,t}$ *only* varies with aggregate output. The empirical results in section 2 indicate, however, that $\pi_{y,t}$ not only depends on output, but also depends (negatively) on beginning-of-period aggregate inventories. To capture both aspects the following specification for $\pi_{y,t}$ is considered:

$$\pi_{y,t} = \underline{\pi}_y + \zeta_y \left(Y_t - \underline{Y}\right) + \zeta_x \left(X_{t-1} - \underline{X}\right) \text{ with } \zeta_y > 0,\, \zeta_x < 0. \tag{50}$$

The values of ζ_y, ζ_x, and ω_0 are chosen to match the observed volatility of employment, the observed cyclical behavior of $\pi_{y,t}$, *and* the observed value for the volatility of sales relative to the volatility of output. Table 5 reports unconditional business cycle moments and figure 6 displays the impulse response functions (IRFs).

The role of inventories for GDP fluctuations. As documented in table 5, this version of the model also generates the right ordering for the volatility of consumption, investment, and output. At the calibrated parameter values, the share of investment in inventories for cyclical fluctuations in GDP is equal to 0.240 when ρ equals 0.7 and 0.259 when $\rho = 0.95$. Both are fairly close to the observed share which is equal to 0.193. Moreover, at the calibrated parameter values the model predicts correctly (again) that inventories and sales are positively correlated at business cycle frequencies and negatively correlated at high frequencies.

Why this version can match the inventory and sales facts. As pointed out in the previous subsection, $\pi_{y,t}$ cannot respond too strongly to changes in real activity, because sales would be more volatile than output if the response is large enough. On the other hand, the response has to be sufficiently strong to ensure that $\pi_{y,t}$ is sufficiently volatile. The dilemma of matching both properties can be solved by letting $\pi_{y,t}$ depend positively on real activity (that is, $\zeta_y > 0$) *and*—as indicated by the empirical findings discussed in section 2—negatively on beginning-of-period aggregate inventories (that is, $\zeta_x < 0$). In fact, with the appropriate choice of ζ_y and ζ_x the model can exactly match the observed volatility and procyclical behavior of $\pi_{y,t}$ (and, thus, match the observed cyclical behavior of the inventory-sales ratio) as well as exactly match the observed volatility of sales relative to the volatility of output. Additional support for the specification used can be found in the fact that the calibrated values for ζ_y and ζ_x are not that different from the empirical estimates discussed in section 2. For example, when $\rho = 0.95$, then the calibrated values are 0.161 and -0.191 for ζ_y and ζ_x, respectively. The empirical estimates for these two parameters are equal to 0.25 and -0.14.[41]

What does the calibrated specification for $\pi_{y,t}$ imply for the behavior of $\pi_{y,t}$ following a shock to Z_t. The results are given in the two panels of the bottom row of figure 6. Similar to the results with $\zeta_x = 0$, $\pi_{y,t}$ displays a sharp drop when Z_t is hit by a negative shock. In contrast to the results with $\zeta_x = 0$, $\pi_{y,t}$ recovers rapidly and goes *above* its pre-shock value as the reduction in aggregate inventories puts upward pressure on $\pi_{y,t}$. The result that the response of $\pi_{y,t}$ switches signs makes it possible to have a sufficiently volatile $\pi_{y,t}$ while at the same time sales do not become too volatile.

The role of the goods-market friction again. Compared with other models in the literature that incorporate inventories into business cycle models, the model developed here is remarkably simple. Despite its simplicity it can generate key facts about inventories and captures the observed importance of investment in inventories for fluctuations in aggregate output. The question arises whether goods-market frictions are an important

[41] Since the regression is affected by endogeneity issues, the estimates of ζ_y and ζ_x should be interpreted with care, but these theoretical results suggest that a more causal interpreted may not be that unreasonable.

channel through which shocks get magnified and propagated when the model matches all key facts regarding the joint behavior of inventories, sales, and output.

Figure 6 plots the employment and output IRFs at the calibrated values for ζ_y and ζ_x and when ζ_y is set as high as possible without having explosive responses, keeping ζ_x fixed. Resembling the results in the section 5.1, employment and output responses are larger (smaller) and more (less) persistent at higher (lower) values of ζ_y. Thus, by increasing ζ_y the model can magnify and propagate shocks, but an increase in ζ_y above its calibrated value comes at the cost of doing worse in terms of matching the observed behavior of inventories. In particular, sales become too volatile relative to output.

The question arises how the model in which $\pi_{y,t}$ is constant compares to the model in which $\pi_{y,t}$ responds to real activity and accumulated inventories as indicated by the calibrated values for ζ_y and ζ_x. That is, how important are changes in goods-market efficiency when the model is calibrated to consistent with the joint behavior of inventories, sales, and output. The IRFs for the case when both ζ_y and ζ_x are equal to zero are also plotted in figure 6. The figure shows that eliminating the calibrated fluctuations in $\pi_{y,t}$ results in *more* magnification and *more* persistence, whereas the opposite was found in the previous subsection. The reason is the following. Consistent with the results in the previous subsection, eliminating the positive dependence of $\pi_{y,t}$ on real activity leads to less magnification and persistence. Eliminating the negative dependence of $\pi_{y,t}$ on aggregate inventories, however, leads to *more* magnification and persistence and this effect turns out to be stronger. The latter effect is only slightly stronger and the employment and output IRFs based on the calibrated specification for $\pi_{y,t}$ are quite similar to the IRFs based on a constant value for $\pi_{y,t}$. Although the richer specification for $\pi_{y,t}$ makes it possible to match the key facts regarding the behavior of inventories, sales, and output, it also means that variation in this measure of the goods-market friction no longer works as a mechanism to magnify and propagate shocks. The concluding section points out that this does not necessarily mean that goods-market frictions do not play an important role in the transmission of shocks, but this role does seem to be restricted by the observed behavior of inventories. At least in this type of model without any other type of friction such as sticky prices.

6 Goods-market frictions, the verdict

The presumption that frictions in goods markets and frictions in labor markets, and especially their interaction, are important for business cycles seems reasonable. If frictions prevent goods market from working efficiently, then this is likely to affect firms' sales and firms' hiring decisions. Similarly, if labor markets do not work efficiently, then this will affect the job-finding rate, which in turn will affect goods-market activity. This paper formalizes this idea and shows that a model with goods and labor-market frictions can quite easily magnify and propagate shocks. Moreover, the model can also replicate key aspects of the behavior of inventories, sales, and output. The problem is that it cannot do both at the same time. Does this mean that realistic goods-market frictions do not change the dynamics of business cycles very much and that there is, thus, not much point in incorporating a goods-market friction in business cycle models?

Before addressing these questions, the key aspect of the restrictions that observed inventories, sales, and output data impose on changes in the goods-market friction is highlighted. Suppose that a negative shock hits the economy. If goods-market frictions are procyclical, then this would mean that such a negative shock would impede sales. The data imply, however, that firms manage to let output drop by *more* than sales. This *seems* to indicate that firms are quite efficient in scaling down the size of operations during downturns. Moreover, if output drops by more than sales, then the probability to sell, i.e., the severity of the goods-market friction, cannot have worsened too much. That is, the level of sales are not that bad relative to the level of output. If the goods-market friction would worsen too much, then a negative shock would lead to an *increase* in inventories and the drop in sales would *exceed* the drop in output.

It is still a good idea to incorporate goods-market frictions, since—as documented in this paper—a simple goods-market friction can match key facts about inventories. Given that changes in the investment in inventories are known to be important for GDP fluctuations, it makes sense to include inventories in business cycle models.

Now consider the question whether the results in this paper indicate that changes in goods-market frictions are unlikely to be quantitatively important for aggregate fluctuations. The provision of many types of services does not allow for inventories. If a hairdresser has no customers, then this does not lead to an increase in inventories. If there are no inventories, then the observed behavior of inventories cannot impose restrictions on the properties of the goods-market friction like inventories do in this paper. But the question arises whether the behavior of goods-market frictions would be very different for services than for manufacturing and wholesale.

Another reason why goods market frictions could be more important than the results in this paper indicate is that the cyclicality of the goods-market friction measure used in this paper understates the procyclical behavior of the true goods-market friction, because it is based on *actual* output instead of *potential* output. To explore this possibility, consider the following simple example. During normal times, firms produce 100 goods, start the period with 100 goods in inventories, and sell 100 goods. Thus, the sell probability is equal to one-half. In addition, suppose that firms would like to reduce output to 80 goods when the economy is hit by a negative shock *and* the sell probability would remain equal to one-half. If the sell probability would indeed remain constant, then sales would drop by 10 to 90, which is less than the drop in output, and inventories would drop to 90. Both properties are consistent with the data. Now suppose that the sell probability does not remain equal to one-half but drops to one third during an economic downturn. Such a drop is far bigger than the ones considered in this paper. If the firms would still produce 80, then sales would drop to 60, i.e., one third of 180 (80 produced goods and 100 from inventories). Inventories would increase and the drop in sales is bigger than the drop in output. Both facts are inconsistent with the data. But now suppose that firms can choose to keep labor idle and that there is some benefit of doing so.[42] Faced with a sharp drop in sales, one could argue that the firm should lower output further, say to 20 units and enter the market this period with 20 newly produced goods and 100 goods in inventories. If the firm still sells 60, then the *observed* value for the sell probability would be equal to

[42] The benefit could be a reduction in material costs or a direct utility benefit of working less.

one-half, that is, the observed goods-market friction would show no change even though the firm faces a sharp reduction in the sell probability if one considers actual sales relative to what the firm could produce given the size of its workforce.

Unfortunately, there are several problems with this reasoning. First, in this numerical example the amount the firm can sell does not depend on the amount of goods it has available. That is, sales are kept constant at 60 when production is reduced. But the idea of the goods-market friction is that mismatch between what producers produce and what consumers want is smaller when markets are bigger. More importantly, if firms can lower actual production during recessions without negatively affecting sales, then the question arises why they would not do so during normal times? If output can be reduced without negatively affecting sales, then firms could lower production during normal times as well, for example, to a level of 50 units, which—if sales remain fixed at 100—would imply that the probability to sell increases from one-half to two-thirds. One would have to argue that this increase in efficiency only happens during downturns, perhaps because operating efficiently is only essential during downturns or the chance of stockouts are less problematic during downturns.

Finally, consider the possibility that inventories drop so much during economic downturns and the sell probability does not drop by that much exactly because the supply of goods falls sharply during down turns. This may very well be the case, but if—in the end—the sell probability does not drop by that much, then this small increase in the severity of the goods-market friction can only play a small part in explaining why supply drops by so much.

A Data sources

The analysis is based on quarterly data from 1967Q1 to 2012Q1. Data are from the NIPA tables of the Bureau of Economic Analysis (BEA). All data are measured in chained 2005 dollar and are seasonally adjusted. Gross Domestic Product (GDP) is taken from table 1.1.6. The GDP data were last revised on June 28 2012.

The data based on final sales uses as inputs: nonfarm inventories to final sales, nonfarm inventories to final sales of goods and structures, and nonfarm inventories. Sales data and the goods-market efficiency measure are constructed using these series. Data are from table 5.7.6A (data up to 1997) and table 5.7.6B (data from 1997 onward). The data up to 1997 are based on the Standard Industrial Classification (SIC) and the data from 1997 are based on the North American Industry Classification System (NAICS). The change in classification system has no effect on these aggregate series. The data from table 5.7.6A were last revised August 11 2011. The data from table 5.7.6B were last revised June 28 2012.

The disaggregated sector data uses as inputs: end-of-period manufacturing and trade inventories and manufacturing and trade sales. The inventory-sales ratio and the goods-market efficiency are constructed using these series. The inventory data are from table 1AU2 (data up to 1997 based on SIC) and table 1BU (data from 1997 onward based on NAICS). The overlapping data in 1997 are used to rescale the data series and eliminate the discontinuity. The sales data are from table 2AU (data up to 1996 based on SIC) and table 2BU (data from 1997 onward based on NAICS). No overlapping data are available. Therefore, hypothetical 1997Q1 SIC-based observations are obtained by extrapolation. The hypothetical 1997Q1 SIC-based observations and the actual 1997Q1 NAICS observations are used to rescaled the series and eliminate the discontinuity. The results presented here are based on the case when the growth rates from 1996Q3 to 1996Q4 is used to construct the hypothetical 1997Q1 observations. Alternatives based on growth rates from the 1996Q1-1998Q4 period give very similar results. The data from tables 1AU2, 2AU, 1BU, and 2BU were last revised August 11 2011, August 5 2009, June 1 2012, and June 1 2012, respectively.

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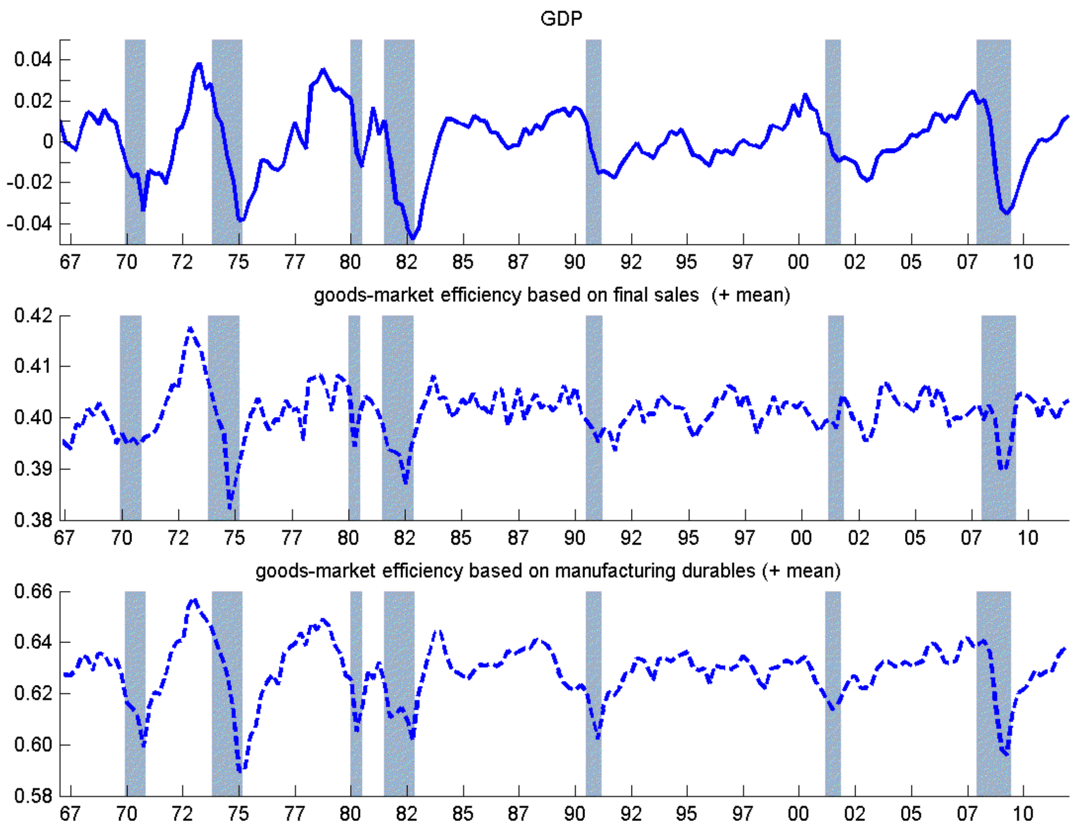
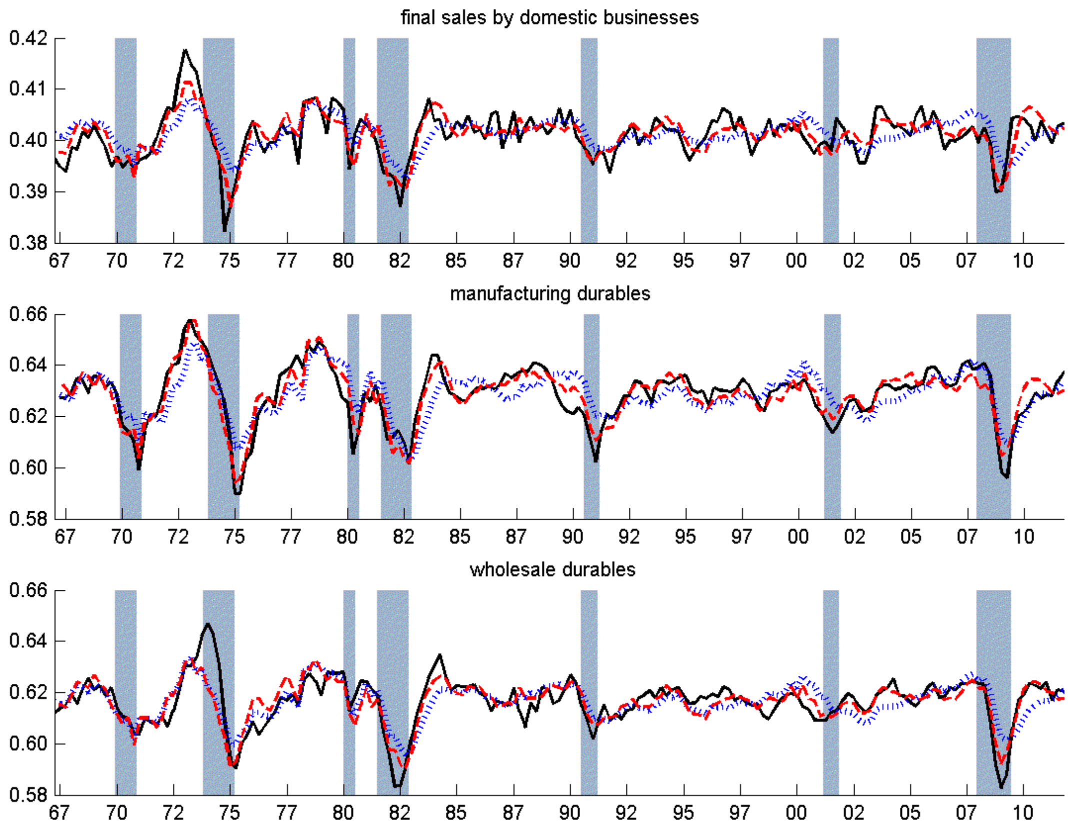
Figure 1: Cyclical behavior of goods-market efficiency



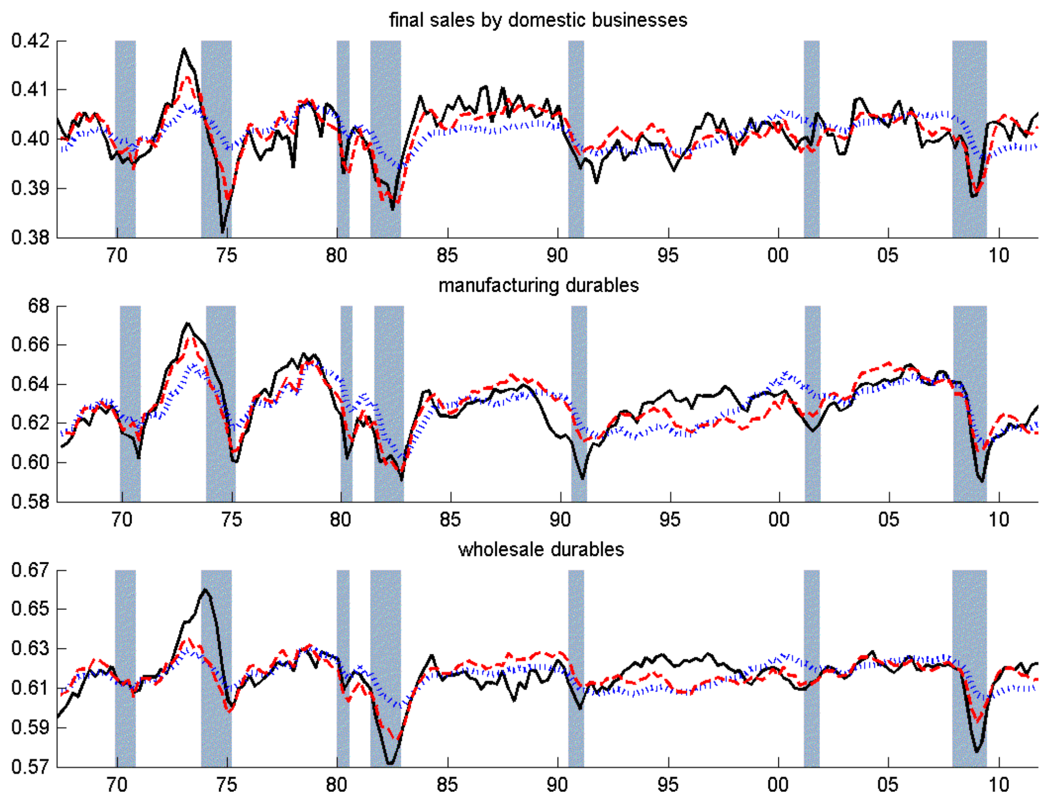
Notes: Each panel plots the cyclical component of the indicated variable. Means of the original series are added to the bottom two panels.

Figure 2: Fitted goods-market efficiency (detrending with the HP filter)



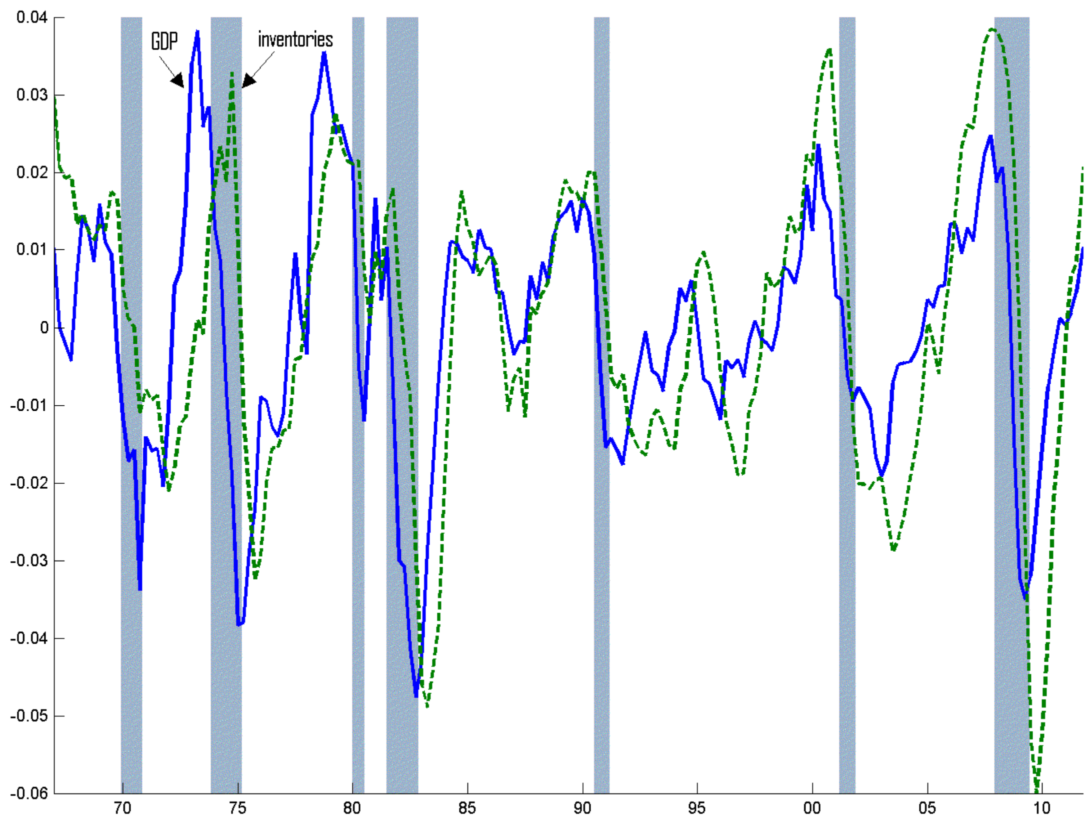
Notes: Each panel plots for the indicated market the cyclical component of goods-market efficiency (solid line), the fitted values from a regression using cyclical GDP (dotted line), and the fitted values from a regression using cyclical GDP and lagged cyclical inventories.

Figure 3: Fitted goods-market efficiency (detrending with a deterministic trend)



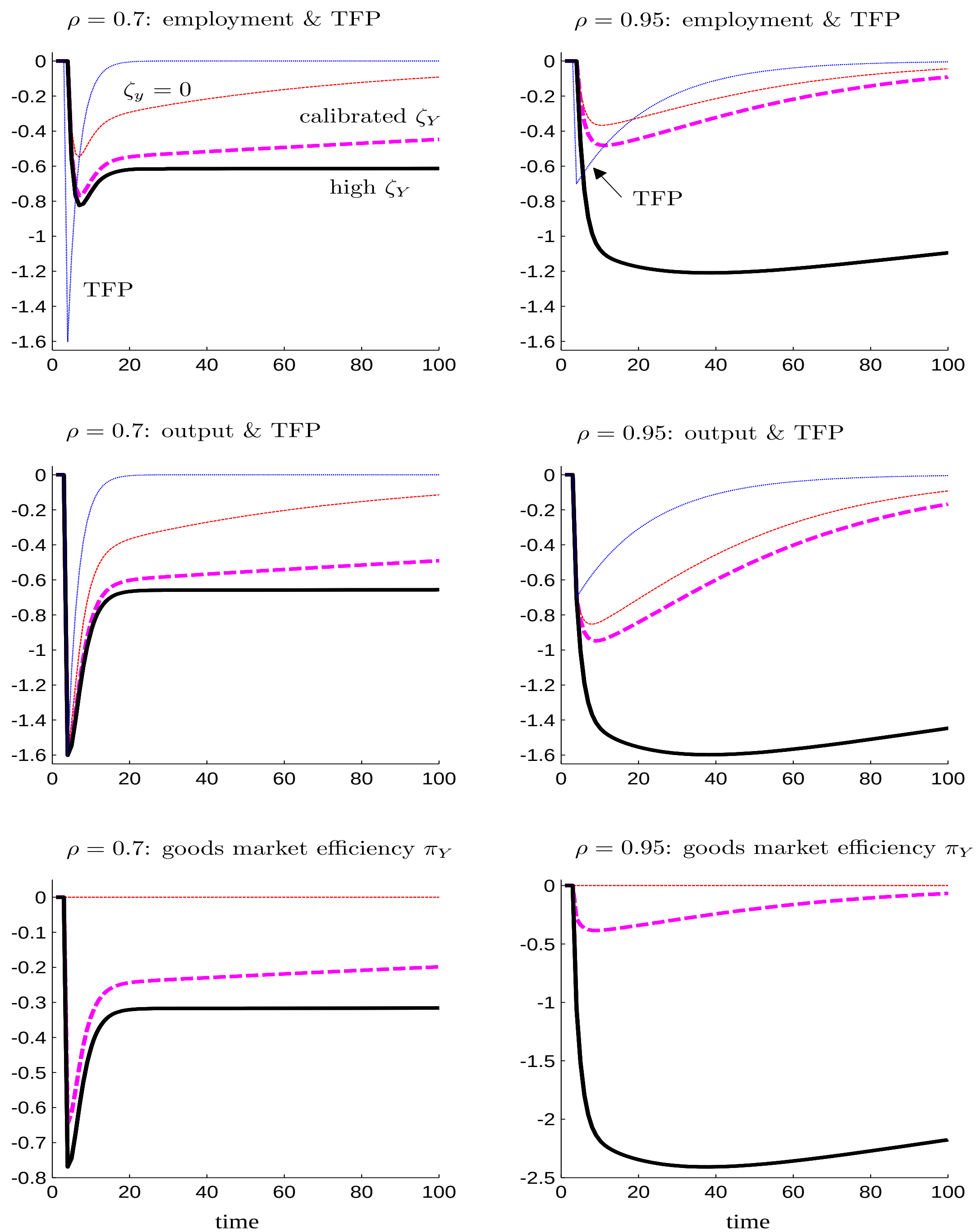
Notes: Each panel plots for the indicated market the cyclical component of goods-market efficiency (solid line), the fitted values from a regression using cyclical GDP (dotted line), and the fitted values from a regression using cyclical GDP and lagged cyclical inventories.

Figure 4: Cyclical behavior of GDP and inventories



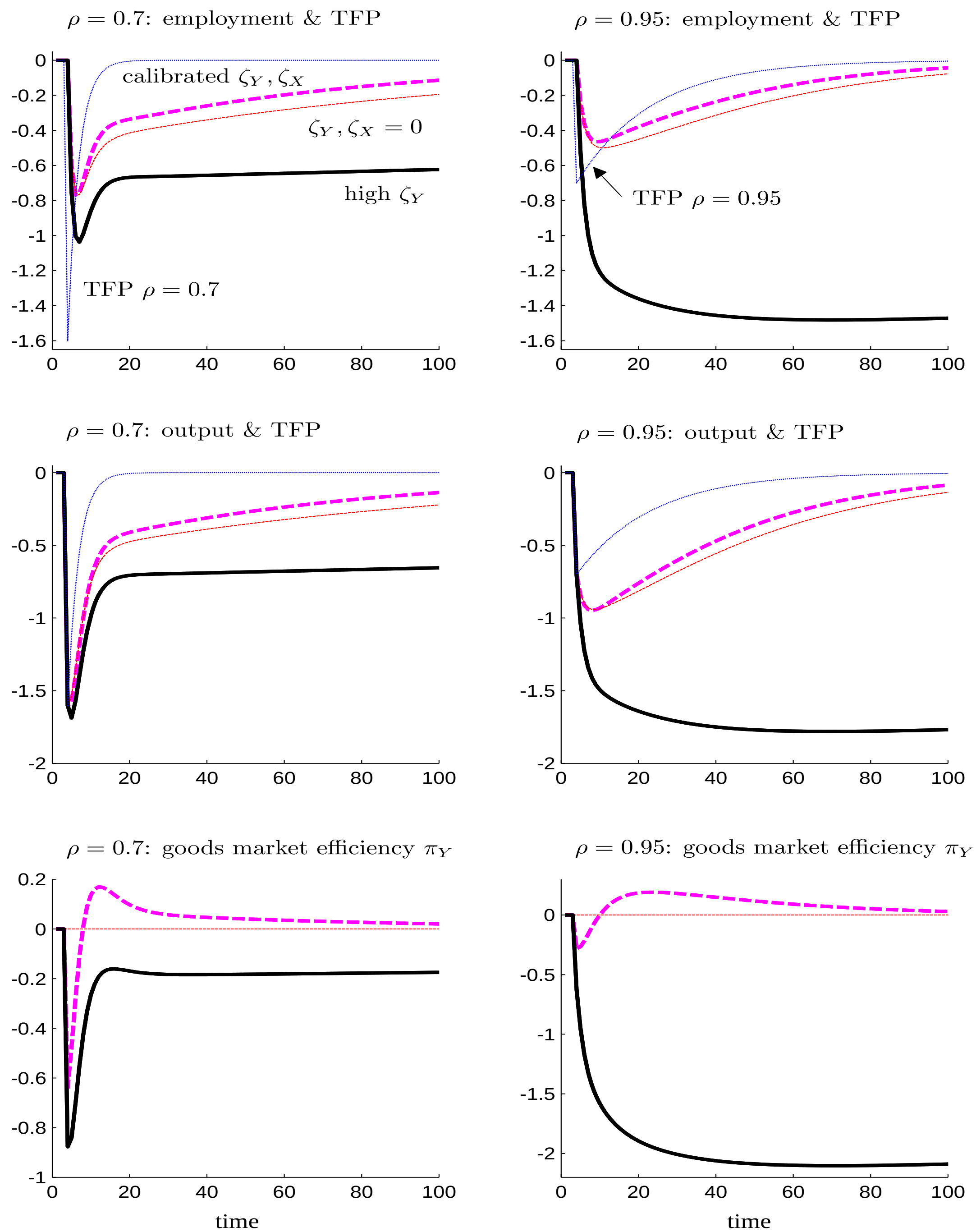
Notes: Data are detrended using the HP filter.

Figure 5: IRFs when not all key inventory facts are matched



Notes: Each panel plots the responses to a productivity shock. The IRF labeled "calibrated ζ_y" corresponds to the case when ζ_y and ω_0 are chosen to match σ_N/σ_Y and σ_{π_y}/σ_Y. This version of the model does not match the observed value of σ_S/σ_Y.

Figure 6: IRFs when key inventory facts are matched



Notes: Each panel plots the responses to a productivity shock. The IRF labeled "calibrated ζ_y,ζ_x" corresponds to the case when ζ_y, ζ_x, and ω_0 are chosen to match σ_N/σ_Y, σ_S/σ_Y, and σ_{π_y}/σ_Y.

Table 1: Summary statistics - Private non-farm inventories and final sales

	total	goods + structures
$\rho_{X,S}$	0.632	0.648
$\rho_{X,S}$, $BP_{\leq 4Q}$	-0.364	-0.358
$\rho_{X,S}$, $BP_{\leq 8Q}$	-0.269	-0.270
$\rho_{\Delta X,S}$	0.356	0.361
σ_S/σ_Y	0.909	0.902
$\rho_{X,S}$, $BP_{\leq 4Q}$	1.033	0.970
$\rho_{X,S}$, $BP_{\leq 8Q}$	1.006	0.972
mean $\pi_{y,t}$	0.550	0.401
mean X_t/S_t	0.821	1.498
σ_{π_y}	0.0041	0.0047
σ_{π_y}/σ_S	0.215	0.184
ρ_{π_y,Y^*}	0.347	0.575
$\rho_{\pi_y,Y}$	0.362	0.607
$\rho_{\pi_y,X_{-1}}$	-0.508	-0.251

Notes: $BP_{\leq NQ}$ indicates that the band-pass filter is used to extract that part of the series that is associcated with fluctuations with a period less than N quarters. All other second-order moments are for HP-detrended data. σ_i is the standard deviation of variable i; $\rho_{i,j}$ is the correlation coefficient of variables i and j; S stands for sales, X stands for inventories, Y stands for GDP, Y^* is the output measure for the group of firms considered (constructed using the sales and inventory data), and $\pi_y = S/(Y + X_{-1})$ is the measure of goods-market efficiency.

Table 2: Summary statistics - Sectoral inventory and gross sales data

	manufacturing		wholesale		retail
	durable	non-durable	durable	non-durable	
$\rho_{X,S}$	0.416	0.338	0.646	0.434	0.687
$\rho_{X,S}$, $BP_{\leq 4Q}$	0.079	-0.104	-0.004	0.056	-0.159
$\rho_{X,S}$, $BP_{\leq 8Q}$	-0.121	0.078	0.098	0.262	-0.167
$\rho_{\Delta X,S}$	0.626	0.330	0.449	0.049	0.231
σ_S/σ_Y	0.973	0.977	0.964	0.985	0.943
$\rho_{X,S}$, $BP_{\leq 4Q}$	0.972	0.945	0.781	0.902	0.922
$\rho_{X,S}$, $BP_{\leq 8Q}$	0.978	0.931	0.890	0.936	0.962
mean π_y	0.628	0.732	0.616	0.786	0.683
mean X/S	0.594	0.367	0.630	0.274	0.465
σ_{π_y}	0.0113	0.0049	0.0096	0.0043	0.0043
σ_{π_y}/σ_S	0.22	0.19	0.18	0.18	0.17
ρ_{π_y,Y^*}	0.812	0.744	0.759	0.331	0.323
$\rho_{\pi_y,Y}$	0.753	0.524	0.718	0.085	0.058
$\rho_{\pi_y,X_{-1}}$	-0.373	-0.402	-0.145	-0.390	-0.356

Notes: $BP_{\leq NQ}$ indicates that the band-pass filter is used to extract that part of the series that is associcated with fluctuations with a period less than N quarters. All other second-order moments are for HP-detrended data. σ_i is the standard deviation of variable i; $\rho_{i,j}$ is the correlation coefficient of variables i and j; S stands for sales, X stands for inventories, Y stands for GDP, Y^* is the output measure for the group of firms considered (constructed using the sales and inventory data), and $\pi_y = S/(Y + X_{-1})$ is the measure of goods-market efficiency.

Table 3: Cyclicality of observed goods-market efficiency

	$\pi_{y,t} = \zeta_y Y_t + \zeta_x X_{t-1}$			$\pi_{y,t} = \zeta_y Y_t$
	ζ_y	ζ_x	R^2	R^2
HP detrending				
final sales	0.25	-0.14	0.67	0.38
gross sales				
dur. manufacturing	0.60	-0.20	0.82	0.57
nondur. manufacturing	0.21	-0.17	0.60	0.27
dur. wholesale	0.51	-0.12	0.66	0.52
nondur. wholesale	0.06	-0.07	0.19	0.006
retail	0.13	-0.11	0.27	0.004
detrending with time trend				
final sales	0.25	-0.13	0.67	0.27
gross sales				
dur. manufacturing	0.52	-0.16	0.72	0.50
nondur. manufacturing	0.16	-0.13	0.50	0.18
dur. wholesale	0.42	-0.11	0.51	0.29
nondur. wholesale	0.18	-0.13	0.57	0.21
retail	0.19	-0.11	0.45	0.00

Notes: The last column displays the R^2 when goods-market efficiency, $\pi_{y,t}$, is projected on GDP, Y_t, only. The other three columns display the projection coefficients and the R^2 when $\pi_{y,t}$ is projected on GDP and beginning-of-period t inventories, X_{t-1}. All series are detrended by the indicated detrending procedure.

Table 4: Results when not all key inventory facts are matched

	data	*model with* $\rho_{Z,Z_{-1}} = 0.7$			*model with* $\rho_{Z,Z_{-1}} = 0.95$		
		$\zeta_y, \omega_0, \omega_1$ calibrated	$\zeta_y = 0$	high ζ_Y	$\zeta_y, \omega_0, \omega_1$ calibrated	$\zeta_y = 0$	high ζ_y
				parameter values			
ζ_y		0.162	0	0.193	0.162	0	0.600
ζ_x		0	0	0	0	0	0
ω_0		0.993	0.993	0.993	0.970	0.970	0.970
				calibrated moments			
σ_N/σ_Y	0.466	=	0.357	0.499	=	0.386	0.732
σ_{π_Y}/σ_Y	0.162	=	0	0.189	=	0	0.566
σ_S/σ_Y	0.901	1.006	0.775	1.064	1.045	0.853	1.823
				inventory properties			
$\rho_{X,S}$	0.648	0.674	0.845	0.644	0.803	0.913	-0.509
$\rho_{X,S}$, $BP_{\leq 4Q}$	-0.358	-0.690	-0.485	-0.700	-0.602	-0.364	0.485
$\rho_{X,S}$, $BP_{\leq 8Q}$	-0.270	-0.086	0.286	-0.118	0.010	0.369	0.123
σ_{XY}/σ_Y^2	0.193	0.149	0.384	0.108	0.094	0.316	-0.461
				standard business cycle statistics			
σ_C/σ_Y	0.535	0.338	0.238	0.367	0.447	0.354	0.896
σ_I/σ_Y	3.554	3.710	2.906	3.935	3.199	2.676	12.431
				autocorrelation unfiltered series			
$\rho_{N,N(-1)}$	-	0.982	0.9153	0.994	0.993	0.989	0.999
$\rho_{Y,Y(-1)}$	-	0.997	0.984	0.999	0.996	0.995	1.000

Notes: This table reports summary statistics of model-generated data and the empirical counterparts. $BP_{\leq NQ}$ indicates that the band-pass filter is used to extract that part of the series that is associated with fluctuations with a period less than N quarters. All other second-order moments are for HP-detrended data. σ_i is the standard deviation of variable i; $\rho_{i,j}$ is the correlation coefficient of variables i and j; S stands for sales, X stands for inventories, Y stands for GDP, Y^* is the output measure for these firms data (constructed using the sales and inventory data), and $\pi_y = S/(Y + X_{-1})$ is the measure of goods-market efficiency. $\rho_{Z,Z_{-1}}$ is the autoregressive coefficient in the law of motion for productivity, Z_t. For both values of $\rho_{Z,Z_{-1}}$, the table has three columns. The first column gives the results when ζ_y and ω_0 are chosen to match σ_N/σ_Y and σ_{π_y}/σ_Y. Not matched is the value of σ_S/σ_Y. The second column gives the results when ζ_y is set equal to 0. The third column gives the results when ζ_y is set to the highest possible value for which model data are non-explosive. "=" indicates that this model characteristic matches its empirical counterpart by construction.

Table 5: Results when all key inventory facts are matched

	data	*model* $\rho = 0.7$			*model* $\rho = 0.95$		
		$\zeta_y, \zeta_x, \omega_0$ calibrated	$\zeta_y = 0$ $\zeta_x = 0$	high ζ_y	$\zeta_y, \zeta_x, \omega_0$ calibrated	$\zeta_y = 0$ $\zeta_x = 0$	high ζ_y
				parameter values			
ζ_y	0.25	0.161	0	0.220	0.161	0	0.355
ζ_x	-0.14	-0.178	0	-0.178	-0.191	0	-0.191
ω_0	-	0.993	0.993	0.993	0.980	0.980	0.980
				calibrated moments			
σ_N/σ_Y	0.466	=	0.474	0.582	=	0.488	0.757
σ_{π_y}/σ_Y	0.162	=	0	0.211	=	0	0.314
σ_S/σ_Y	0.901	=	0.788	1.046	=	0.861	2.521
				inventory properties			
$\rho_{X,S}$	0.648	0.327	0.858	0.326	0.433	0.919	-0.228
$\rho_{X,S}$, $BP_{\leq 4Q}$	-0.358	-0.741	-0.456	-0.721	-0.519	-0.323	0.128
$\rho_{X,S}$, $BP_{\leq 8Q}$	-0.270	-0.362	0.903	-0.351	-0.215	0.340	0.050
σ_{XY}/σ_Y^2	0.193	0.240	0.372	0.118	0.259	0.308	-0.265
				standard business cycle statistics			
σ_C/σ_Y	0.535	0.252	0.262	0.353	0.359	0.378	1.008
σ_I/σ_Y	3.554	3.571	2.910	3.92	2.903	2.724	16.900
				autocorrelation unfiltered series			
$\rho_{N,N(-1)}$	-	0.933	0.949	0.991	0.990	0.992	1.000
$\rho_{Y,Y(-1)}$	-	0.977	0.987	0.998	0.993	0.995	1.000

Notes: This table reports summary statistics of model-generated data and the empirical counterparts. $BP_{\leq NQ}$ indicates that the band-pass filter is used to extract that part of the series that is associated with fluctuations with a period less than N quarters. All other second-order moments are for HP-detrended data. σ_i is the standard deviation of variable i; $\rho_{i,j}$ is the correlation coefficient of variables i and j; S stands for sales, X stands for inventories, Y stands for GDP, Y^* is the output measure for these firms data (constructed using the sales and inventory data), and $\pi_y = S/(Y + X_{-1})$ is the measure of goods-market efficiency. $\rho_{Z,Z_{-1}}$ is the autoregressive coefficient in the law of motion for productivity, Z_t. For both values of $\rho_{Z,Z_{-1}}$, the table has three columns. The first column gives the results when ζ_y, ζ_x, and ω_0 are chosen to match σ_N/σ_Y, σ_S/σ_Y, and σ_{π_y}/σ_Y. The second column gives the results when ζ_y and ζ_x are set equal to 0. The third column gives the results when ζ_y is set to the highest possible value for which model data are non-explosive. "=" indicates that this model characteristic matches its empirical counterpart by construction.