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Abstract

Beginning in the mid-1980s, the nature of U.S. business cycles changed in important ways, as made evident by distinctive shifts in the comovement and relative volatilities of labor productivity, hours, output, and inventories. Unlike the widely documented change in absolute volatility over that period, known as the Great Moderation, these shifts in comovement and relative volatilities persist into the Great Recession. To understand these changes, we exploit the fact that inventory data are informative about sources of business cycles. Specifically, they provide additional information relative to aggregate investment regarding firms' intertemporal decisions. In this paper, we show that variations in the discount factor estimated using inventories correlate well with established independent measures of credit market frictions. Furthermore, these variations, which in our model may be interpreted as fluctuations in a generalized investment wedge, play a key role in explaining the shifts in U.S. business cycles observed after the mid-1980s.

Keywords: Business Cycles, Inventories, Investment Wedge, Financial Frictions

JEL Code: E32, E44

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1 Introduction

From the mid-1980s on the U.S. economy has exhibited a considerably lower degree of volatility in key macroeconomic aggregates when compared to earlier periods. This pattern has come to be known as the Great Moderation. What has received less attention in the literature is the fact that the period is also characterized by notable changes in the comovement properties of some of these aggregates. Specifically, labor productivity is no longer procyclical. Moreover, it has switched from comoving positively with hours worked before 1984 to comoving negatively with hours over the post-1984 period.[1] Over the same period, the inventory-sales ratio has switched from markedly countercyclical to acyclical, and the volatility of both inventories and hours relative to output has increased. Unlike the fall in absolute volatility associated with the Great Moderation, these shifts in comovement patterns and relative volatilities continue well into the Great Recession. We argue in this paper that variations in the discount rate, which may stem partially from credit market frictions, have played a key role in explaining not just the Great Recession but, more generally, post-1984 business cycles.

Our work builds on a literature, exemplified by Bils and Kahn (2000), that uses inventory data to inform our understanding of business cycles.[2] Using a formal model with a multi-sector and multi-stage production structure we argue that inventories are informative about factors driving business cycles because they help distinguish between changes in investment induced by variations in (i) the physical return to fixed investment, typically governed by technological opportunities (Fisher, 2006; Greenwood, Hercowitz, and Krusell, 2000), and (ii) the discount rate used to assess future income streams. Our findings indicate that variations in the latter have played an increasingly prominent role in explaining inventory behavior after 1984. Moreover, fluctuations in the discount rate also help explain the reduced comovement between labor productivity and output after that date, commonly referred to as the "labor productivity puzzle". This finding arises because changes in the discount rate also act on labor supply by affecting intertemporal substitution. In general, the results obtained from our model differ from those in the canonical real business cycle (RBC) model without

[1] See Gordon (2010), and Garin, Pries, and Sims (2013)

[2] The study by McConnell and Perez-Quiros (2000) on the decline in US GDP volatility in the early 1980s generated a large literature that investigated changes in inventory management as the primary driver (see also Kahn, McConnell, and Perez-Quiros (2002)). Using the U.S. automobile industry as a case study, Ramey and Vine (2006) show that this can explain the changing behavior of US time series both in terms of volatility and comovement. More recent work, such as Chang, Hornstein, and Sarte (2009), has extended this line of work to account for changes in pricing behavior and mark-ups, building on Bils and Kahn (2000).

inventories in that variations in the discount rate rather than changes in the valuation of leisure have become a significant driver of recent recessions.

We adopt the stage-of-production technology as a way of nesting previous detailed production structures in the RBC literature (Kydland and Prescott 1982, Long and Plosser 1983) while, at the same time, allowing for inventories in a set-up, common in the inventory literature, in which firms trade off the opportunities for intertemporal substitution allowed by inventories with a cost of deviating from an (endogenous) target inventory-sales ratio. The elasticity of substitution between stages of production determines several special cases found in previous work. One of our contributions is that this parameter is estimated using Bayesian methods. One finding in this paper is that the data suggest a fair amount of substitutability, not unlike a linear storage technology.

Our analysis builds on a framework in which allocations are first-best. Within that environment, we study the role of different shocks to the production frontier and to preferences. To the extent that frequent or large changes in preferences are unlikely to be primitive drivers of the business cycle, our finding regarding the more prominent role of variations in the discount rate is suggestive of important distortions in intertemporal markets. In particular, those fluctuations in the discount rate can be alternatively interpreted as fluctuations in a generalized investment wedge. Christiano and Davis (2006) and Buera and Moll (2012) caution, however, that credit market frictions can manifest themselves in wedges other than the investment wedge, and that the investment wedge itself might reflect frictions other than those relevant to financial markets.[3] We show in our model that estimates of the investment wedge by way of a time-varying rate of time preference comove robustly with other independent indicators of financial frictions. This is unlike more conventional measures that abstract from information on inventories, such as that first estimated by Chari, Kehoe, and McGrattan (2007). As measures of financial frictions, we consider the spread between the returns on high and low credit risk bonds, dividend payouts to business owners, Jermann and Quadrini's (2012) estimates of financial shocks, and the Federal Reserve senior loan officer survey of bank standards for commercial and industrial loans. Furthermore, these more conventional indicators of credit market frictions are similar to our estimated investment wedge in that they comove more strongly with output and fixed investment after the start

[3] Buera and Moll (2012) illustrate this point in the context of a model where aggregate savings derive largely from entrepreneurs with heterogeneous productivity and their own credit constraint. In that environment, shocks that intensify credit frictions also affect aggregate TFP and the labor wedge. More generally, Christiano and Davis (2006) make the point that, because frictions can be reflected in several wedges simultaneously, these wedges will generally be cross-correlated.

of the Great Moderation.

A large literature explores the role of financial factors for business cycles, such as Christiano, Motto, and Rostagno (2010), Gilchrist, Sim, and Zakrajsek (2014), Jermann and Quadrini (2012), Shourideh and Zetlin-Jones (2012), and Khan and Thomas (2013). Our paper contributes to this literature and connects it to two other lines of research. The first examines changes in the composition of shocks that affect the economy during the Great Moderation, for instance, Justiniano, Primiceri, and Tambalotti (2010). We share with this latter paper the finding that business cycles during the Great Moderation are largely influenced by shocks that affect investment, but which are not necessarily related to the relative price of investment goods. While these authors consider a New Keynesian setting, we come to this conclusion by way of a model that adheres to the spirit of the early RBC literature in that it explores the implications of technological constraints for business cycle patterns.[4] The second literature we connect with uses wedges as helpful indicators of market frictions, such as Hall (1997), Chari, Kehoe, and McGrattan (2007), and Hsieh and Klenow (2009). In particular, we show that an aggregate investment wedge can correlate well with indicators of financial frictions and, moreover, that the frictions implied by this wedge may have played an increasingly prominent role in driving business cycles over the course of the last decades.

There is relatively little work that underscores changes in inventory behavior before and after 1984. Notable exceptions are Benati and Lubik (2014), who describe changes in inventory behavior over the last century in a time-varying parameter VAR framework, and Iacoviello, Schiantarelli, and Schuh (2011), who study those changes in the context of an estimated general equilibrium model with an emphasis on whether these changes can account for the observed fall in output volatility. We focus instead on whether changes in factors affecting inventory investment also help explain changes in the comovement between output and labor.

This paper is organized as follows. Section 2 highlights some key ways in which the nature of post-war U.S. business cycles has changed after 1984. Section 3 develops a model of business cycles with a generalized production technology and a role for inventory formation. Section 4 discusses the data and estimation. Section 5 presents and discusses our empirical findings. Section 6 compares our estimated variations in the discount rate with other measures of financial frictions, and provides an assessment of the inventory model in which these

[4]Aside from the literature on financial factors and business cycles, our work simultaneously speaks to a growing literature motivated by the labor productivity puzzle. For a recent example that looks at alternative candidate explanations for that puzzle, see Garin, Pries, and Sims (2013).

variations arise. Section 7 concludes.

2 Business Cycles Old and New

Table 1 summarizes changes in the behavior of key U.S. economic aggregates over the post-war era. We focus on output, consumption, investment, hours, and inventories.[5] Inventories are measured as total inventories, including raw materials, work in process, and finished goods. Except for hours, all data is obtained from the Bureau of Economic Analysis and cover the period from 1953Q3 to 2011Q4. Hours data are obtained from the Bureau of Labor Statistics and are constructed as described in Francis and Ramey (2005). We focus on business cycle frequencies and pass the raw data through a standard HP-filter.[6]

Table 1 shows that prior to 1984, labor productivity, defined as output per hour, is strongly procyclical. Its correlation with output is 0.65. Moreover, labor productivity co-moves positively with labor input. In addition, consumption is only a third as volatile as output while, conversely, the standard deviation of investment is more than twice that of output. In broad qualitative terms, these basic properties of U.S. economic aggregates are all easily reproduced in a prototypical one-sector growth model driven solely by Hicks-neutral productivity shocks. Indeed, the ascendancy of the RBC literature starting in the mid-1980s is intimately linked with the behavior of key economic aggregates up to that time, as captured in King, Plosser, and Rebelo (1988).

Table 1 also shows that the inventory-sales ratio prior to 1984 is markedly countercyclical. Its correlation with output is negative at -0.57, which lines up with findings in Bils and Kahn (2000). While the early RBC literature mostly abstracts from inventory behavior, we show in Section 5.1 that the countercyclicality of the inventory-sales ratio can also be supported by productivity shocks in an extension of the RBC framework that allows for inventory formation. Intuitively, a positive productivity shock raises the marginal return to fixed investment relative to inventory investment, so that inventories rise relatively less rapidly than other aggregates.

The behavior of economic aggregates changes considerably after 1984. The standard deviation of output declines by almost half over the period 1984-2008, as do the standard

[5]In this paper, output is defined as the sum of final private expenditures of domestic residents and includes personal consumption expenditures and private investment in both fixed assets and inventories. We exclude government consumption and the trade balance.

[6]The salient changes in the nature of business cycles we consider are robust to different detrending methods, including expressing the data in growth rates.

deviations of consumption and investment, while not quite matching the fall in output volatility. On the whole, the period 1984-2008 has been described as a Great Moderation relative to the period that preceded it. This reduction in volatility dissipates after 2008, with the onset of the Great Recession.

Table 1 further indicates that the Great Moderation period is characterized by significant changes in comovement patterns compared with the pre-1984 period. The procyclicality of labor productivity all but vanishes. Its correlation with output after 1984 falls to 0.06. At the same time, labor productivity switches from comoving positively with hours before 1984 to comoving negatively with hours in the post-1984 era. This fact holds irrespective of the definition of labor input and also holds for employment. Both these changes directly challenge the notion of a business cycle driven primarily by Hicks-neutral productivity shocks in a neoclassical environment. Moreover, Table 1 shows that the volatility of labor input relative to that of output increases by more than 50 percent after 1984, which suggests changes in frictions governing labor markets. Finally, the countercyclicality of the inventory-sales ratio also vanishes in the post-1984 period. At the same time, the volatility of inventories relative to output increases by more than 50 percent.[7]

The shifts in relative volatilities and comovement patterns documented in Table 1 hold throughout the Great Recession, suggesting that this last recession was typical of post-1984 business cycles, albeit on a much larger scale. To address these changes, the next section sets up an environment with multiple sectors and multiple stages of production that features inventories while, at the same time, nesting the rich production structure of detailed RBC models first introduced by Kydland and Prescott (1982) or Long and Plosser (1983).

3 A Framework with Multi-Sector and Multi-Stage Production

We construct a model where shifts in the technology frontier affect business cycles in multiple ways. In particular, we extend the canonical RBC environment of King, Plosser, and Rebelo (1988) to include multiple stages of production, productivity changes that affect sectors differently, and both permanent and temporary shifts in production possibilities. We also consider two types of preference shocks, namely shocks to the rate of time preference used

[7]This increase in relative volatility is distinct from the well-documented secular decline in the inventory-sales ratio in the post-war period.

to assess future income streams and shocks to the disutility of labor, which affect the valuation of leisure. Since observed allocations may differ from first best in practice, the online appendix shows how in our model variations in preferences induced by shocks to the rate of time preference and to the disutility of labor can be interpreted equivalently as fluctuations in "wedges" that distort savings and labor decisions.[8] These "wedges" in turn may arise from frictions that might include nominal rigidities, government regulations that distort labor markets or hinder production possibilities, or commitment problems that constrain the allocation of credit and financial intermediation. This approach allows us to capture an extensive set of changes to the production possibilities frontier that might otherwise be assigned to preference shocks.

At the core of our model is a stage-of-production technology: Firms cannot increase production overnight. Goods delivered on a given date are the result of a lengthy process that starts with planning and design decisions, it involves the coordination of suppliers, the physical production process itself, and then distribution to final retailers and consumers. Throughout the later stages of the process, materials, works in progress, and finished goods sit in trucks or in storage as they are transferred between different suppliers, they wait for complementary parts to arrive, or for the final consumer to enter the store.[9] The link between a stage-of-production technology and inventories was recently noted by Schwartzman (2014). A key contribution of our paper is that we provide an estimate of the elasticity of substitution between stages of production, which was missing from earlier work. This is because our model nests at one extreme, the specification in Kydland and Prescott (1982) which presumes no substitution between stages of production, the specification in Schwartzman (2014) in which the elasticity of substitution is fixed at 1, and a linear storage technology in which the elasticity of substitution is infinite.[10] In all but the extreme case of an infinite elasticity of substitution between stages of production, the model implies a long-run target inventory-sales ratio, as in Kahn (1992), which Iacoviello, Schiantarelli, and Schuh (2011) and Wen

[8]See, in particular, section 4 of Lubik, Sarte, and Schwartzman (2015) which recasts the planning problem with preference shocks described in this paper as a decentralized competitive equilibrium with stochastic distortionary taxes. In section 8 of the appendix, we discuss the implications of these wedges for macroeconomic allocations.

[9]A conservative measure of the overall duration of this process is given by the ratio between inventories and the production of finished goods. In the U.S. as a whole, this measure stands at about two months worth of final sales held in inventories. This number is conservative in that it accounts only for the actual production and distribution stages, but not the early design and planning stages.

[10]Kydland and Prescott (1982) abstract from inventories in their time-to-build approach. This is justified when the technology is meant to capture primarily the time needed to build structures, since incomplete structures are not counted as inventories but as part of the capital stock.

(2011) have extended to a general equilibrium setting. Our model admits these various forms of intertemporal linkages in production while, at the same time, allowing for more conventional input-output linkages.[11]

3.1 Economic Environment

Consider an economy with N distinct sectors of production. At date t, each sector transforms inputs produced in previous dates, $Z_{j,t-s|t}$, into sales, $Y_{j,t}$, of a good j. The subscript $t-s|t$ refers to an input used at date $t-s$ in order to generate sales at date t. Thus, s is the time elapsed between the purchase of the input and the sale of the good. The technology necessary for distribution and sales requires combining inputs produced at various previous dates, $Z_{j,t-s|t}$:

$$Y_{j,t} = \left(B_j \sum_{s=0}^{S} \omega_j (s)^{\frac{1}{\varrho}} Z_{j,t-s|t}^{\frac{\varrho-1}{\varrho}} \right)^{\frac{\varrho}{\varrho-1}}, \ \varrho > 0, \tag{1}$$

where $s = 0, ..., S$; $\omega_j(s)$ are the weights given to each stage of production s in the production of good j, and B_j is a normalizing constant.

As an example, consider the case $S = 2$, where j is an aircraft, to be used by a final customer at $t+2$. This requires the use of inputs at date t , $t+1$, and $t+2$, aggregated in, respectively, $Z_{j,t|t+2}$, $Z_{j,t+1|t+2}$, and $Z_{j,t+2|t+2}$. The first stage, taking place at t, necessitates acquiring varieties of raw materials from different suppliers such as aluminum and other metals and alloys, and moving them to warehouses for storage until different varieties are available to be combined. The combination of inputs used at date t defines $Z_{j,t|t+2}$. In the following stage, at date $t+1$, $Z_{j,t|t+2}$ is cut and formed into components, such as the fuselage, wings, or vertical tail, that will make up the final aircraft using labor and specialized machinery. This labor and machinery constitute $Z_{j,t+1|t+2}$. In the final stage, at $t+2$, the different components of the aircraft are assembled into a finished product that is then extensively tested to gain certification before being flown to final customers. The inputs involved in the testing, distribution, and delivery make up $Z_{j,t+2|t+2}$.[12]

The parameter ϱ in the aggregator function (1) governs the substitutability of the different stages of production. At one extreme, as $\varrho \to 0$, there is no substitution. Raw materials have

[11] For example, Long and Plosser (1983), Dupor (1999), and Foerster, Watson, and Sarte (2011).

[12] As we discuss in detail below, the cost of inputs included in $Z_{t|t+2}$ and $Z_{t+1|t+2}$ are added together into inventories. Thus, we do not strictly differentiate between raw materials, work-in-process, and finished goods. Similarly to Ramey (1989), we treat all inventories as necessary to a broader production process. For a more detailed treatment of different types of inventories, see Humphreys, Maccini, and Schuh (2001).

to be available one full period before they can be cut and formed into components which, in turn, take another full period to be assembled, tested, and delivered to the final consumers. This assumption reproduces the time-to-build technology of Kydland and Prescott (1982). At the other extreme, as $\varrho \to \infty$, it is possible to compensate fully for smaller amounts of materials acquired at t with a more elaborate assembly process at $t+1$. A storage technology is a special case of $\varrho \to \infty$ where the same input mix is used at each stage of production. That is, in order to have an aircraft available at $t+2$, production can either take place at t with the aircraft then stored until $t+2$ (with a proportional depreciation cost governed by $\omega_j(s)$), or take place at $t+2$ with the aircraft sold right away.

In the general case, where $0 < \varrho < \infty$, the technology allows for limited substitution between stages of production. Because the extent of substitution is limited, it is seldom optimal to reduce production to a single stage despite the opportunity cost of time. Consequently, there typically exists a positive steady-state target for the inventory-sales ratio. In that sense, our technology also captures a set up, common in the inventory literature, that combines a linear storage technology with a cost of deviating from some target inventory-sales ratio.

The production of inputs available in a given sector, $Z_{j,t|t+s}$, takes place using a Cobb-Douglas technology that combines capital, $K_{j,t|t+s}$ (warehouses, moving trucks, or machinery), labor, $L_{j,t|t+s}$ (including distribution and sales), and materials produced in other sectors, $M_{ij,t+s}$:

$$Z_{j,t|t+s} = K_{j,t|t+s}^{\alpha_j} \left(\prod_{i=1}^{N} M_{ij,t|t+s}^{\gamma_{ij}} \right) \left(A_{j,t} L_{j,t|t+s} \right)^{1-\alpha_j - \Sigma_{i=1}^{N} \gamma_{ij}}. \tag{2}$$

As emphasized in Long and Plosser (1983), the fact that each sector uses materials from other sectors represents a source of dynamic linkages in the model. The ij subscript in $M_{ij,t|t+s}$ denotes materials from sector i used in the production of sector j goods.

In equation (2), $A_{j,t}$ captures changes in the efficiency with which labor contributes to production. These changes are allowed to operate along three dimensions:

$$A_{j,t} = u_t A_t a_{j,t}, \tag{3}$$

where u_t and $a_{j,t}$ have unit unconditional means. A_t is a common component in all sectors and has permanent effects on Hicks-neutral total factor productivity (TFP), which we model as a unit root process with drift. As such, the growth rate, $g_t = A_t/A_{t-1}$, captures long-run labor-augmenting technological progress that varies over time around a constant mean $g > 1$.

Second, a common disturbance, u_t, accounts for temporary changes in the level of efficiency with which labor is used in production. Finally, some of the changes in production efficiency in a given sector reflect considerations idiosyncratic to that sector, denoted by a_{jt}.

In each sector, j, the capital stock evolves according the law of motion

$$K_{j,t+1} = X_{j,t} + (1-\delta)K_{j,t}, \tag{4}$$

where $X_{j,t}$ denotes investment in sector j and δ is the depreciation rate. Investment in each sector j is produced using the amount $I_{ij,t}$ of sector i output by way of a constant returns to scale technology,

$$X_{j,t} = \Xi_j \prod_{i=1}^{N} I_{ij,t}^{\theta_{ij}}, \ \sum_{i=1}^{N} \theta_{ij} = 1, \tag{5}$$

where Ξ_j is a constant. As in models with investment adjustment costs, equation (5) allows for a non-constant rate of transformation between consumption and investment. Furthermore, just as in Kydland and Prescott (1982), multiple stages of production imply a constraint on the speed with which sales of investment goods can adjust to disturbances.

A representative household derives utility from the consumption of goods produced in every sector according to

$$E_0 \sum_{t=0}^{\infty} \left(\beta^t \prod_{v=0}^{t-1} \zeta_v \right) \left[\kappa \ln C_t + (1-\kappa) \ln(1 - \Upsilon_t L_t) \right], \tag{6}$$

where C_t denotes the consumption aggregate,

$$C_t = \prod_{i=1}^{N} \Lambda C_{j,t}^{\eta_j}, \ \sum_{j=1}^{N} \eta_j = 1, \tag{7}$$

and the η_j's are the shares of consumption of good j in aggregate consumption. The variable L_t represents aggregate labor input and thus must satisfy

$$L_t = \sum_{j=1}^{N} L_{j,t}. \tag{8}$$

In the specification of preferences (6), the variable ζ_v represents a random disturbance shifting the discount rate between subsequent periods, defined by $(\beta\zeta_t)^{-1} - 1$. We show in the online appendix how variations in that discount rate can be interpreted as stemming from variations in a wedge between households' intertemporal rate of substitution and the physical return to investment, specifically a tax on capital income. Similarly, the term Υ_t in (6) shifts the supply of labor and, in the decentralized economy, can be alternatively interpreted as a tax on labor income that, under special assumptions, reduces to the labor wedge measured in previous work.

Finally, each sector is subject to a resource constraint,

$$C_{j,t} + \sum_{i=1}^{N} I_{ji,t} + \sum_{i=1}^{N} M_{ji,t} = Y_{j,t}. \tag{9}$$

Our environment simplifies to the prototype growth model of King, Plosser, and Rebelo (1988) when production does not use dated inputs, $\omega(s) = 0$ for $s > 0$, interlinkages in materials or investment are unimportant, $\gamma_{ij} = \theta_{ij} = 0$, and the economy contains only one sector, $j = 1$. In that case, aggregate output is produced via an aggregate production function described by a Cobb-Douglas technology that uses only contemporaneous inputs.

3.2 National Accounting and Relationships to Data

We now outline how key variables in the model map into corresponding NIPA data by way of corporate and national accounting identities. A key feature of the environment described in the previous section pertains to the implications of our multi-stage production structure for the behavior of inventories. While we analyze our model using the solution to a planner's problem, a decentralized version of the economic environment would feature relative prices that coincide with ratios of Lagrange multipliers obtained from the planner's problem. Therefore, when measuring variables at constant prices, we rely on these multipliers evaluated at the steady state. We choose the normalizing constants B_j and Ξ_j in the production technology, and Λ in preferences, such that relative prices are equal to one in the steady state.

Given that the total value of goods produced in the economy, Z_t, is the sum of output across all sectors and all stages of production with future completion dates t to $t+S$, we have

$$Z_t = \sum_{j=1}^{N} \sum_{s=0}^{S} Z_{j,t|t+s}. \tag{10}$$

Aggregate value added, or gross domestic product (GDP), V_t, is the total value of production less the value of intermediate inputs, $V_t = Z_t - \sum_{i=1}^{N} \sum_{j=1}^{N} M_{ij,t}$. Sales in sector j are given by

$Y_{j,t}$, so that aggregate sales are $\mathcal{S}_t = \sum_{j=1}^{N} Y_{j,t}$. Similarly, sales of final goods, or final sales, $\mathcal{FS}_t$, amount to total sales less the value of materials $\mathcal{FS}_t = \sum_{j=1}^{N} Y_{j,t} - \sum_{i=1}^{N}\sum_{j=1}^{N} M_{ij,t}$. Let N_t denote the stock of inventories at date t, and let ΔN_t be inventory investment. The NIPA definition of inventory investment, namely gross domestic product less final sales is:

$$\Delta N_t = V_t - \mathcal{FS}_t. \tag{11}$$

Given the technology in (1), sales in period t rely on inputs produced in previous periods. In particular, at date t, the corporate accounting definition of the cost of goods sold, denoted $\mathcal{C}_t$, reflects the cost of inputs used between dates $t - S$ and t,

$$\mathcal{C}_t = \sum_{j=1}^{N}\sum_{s=0}^{S} Z_{j,t-s|s}. \tag{12}$$

Since our technology satisfies constant returns to scale, the cost of goods sold in our model is simply the value of sales, $\mathcal{C}_t = \mathcal{S}_t$.[13] Adding and subtracting materials to the right-hand-side of equation (11), inventory investment can then be expressed as $\Delta N_t = Z_t - \mathcal{C}_t$. Substituting in the definitions of Z_t and $\mathcal{C}_t$ shows that inventory investment is closely tied to the multi-stage nature of production,

$$\Delta N_t = \sum_{j=1}^{N}\sum_{s=0}^{S} Z_{j,t|t+s} - \sum_{j=1}^{N}\sum_{s=0}^{S} Z_{j,t-s|s}. \tag{13}$$

By iterating equation (13) forward, we can recover the stock of inventories.

4 Calibration and Estimation

Our empirical approach combines elements of calibration and likelihood-based estimation. We choose to calibrate a large number of the preference and technology parameters since information on their values is readily available and there is substantial consensus in the literature. Parameters that are not easily calibrated are estimated using a Bayesian approach. Our empirical analysis remains firmly wedded to the calibration literature and thereby facilitates the comparison of our results with that large body of work. At the same time,

[13] In practice, these might differ slightly because conventional corporate accounting does not take into account the opportunity cost of committing resources to production for a good to be sold at a later date reflected in the interest rate. However, this distinction is quantitatively small.

we are able to make inferences about the structural shocks underlying the economy in a model-consistent manner.

A time period in the model is one quarter. We set the per-capita steady-state growth rate equal to 2 percent, the depreciation rate of fixed capital to 10 percent, and the steady-state discount factor β to 0.96, all on an annual basis. The parameter κ governing the share of leisure in utility is chosen so that in steady state leisure is approximately two-thirds of the available time endowment. We rely on the input-output tables and the capital flow tables to parameterize the contribution of different sectors to inputs and capital formation. In line with the discussion on National Accounting in Section 3.2, we follow Schwartzman (2014) and use data on the inventory-sales ratio to calibrate the weights associated with the different stages of production, $\omega_j(s)$. We assume that these weights decline exponentially with s and choose a rate of decline $\frac{\omega_j(s+1)}{\omega_j(s)}$ that matches the average inventory-sales ratio in each sector over the entire sample period. The rate of decline is slower in the durable goods sector, since this sector can make greater use of inventories. With the exception of cross-sectoral weights, all calibrated parameters are stated in Table 2.[14]

We then estimate the remaining parameters using a Bayesian approach, specifically the parameters of the unobservable exogenous shock processes and the elasticity of substitution between stages of production, ϱ. The latter cannot be easily calibrated as there is virtually no prior information. The structural estimate of ϱ will therefore provide independent insight into the nature of the intersectoral linkages and the production processes in the U.S. economy. We assume that all temporary shocks follow AR(1) processes and we allow for correlation in their innovations.

The benchmark specification consists of four stages of production and two sectors, s in Iacoviello, Schiantarelli, and Schuh (2011): one sector corresponds to durables, the other to nondurables.[15] As described in sections 3.1, we allow for five shocks: three shocks to productivity, one shock to the disutility of labor, and a shock to the rate of time preference. The exogenous forces that drive measured TFP therefore consist of: (i) a transitory disturbance that augments labor by the same proportion in both sectors; (ii) a permanent disturbance that augments labor proportionally in both sectors; and (iii) a sectoral shock that only affects

[14]In addition, Tables 1 and 2 in the online appendix provide all calibrated parameters and the covariance matrices of the shocks implied by the estimation. The appendix also provides a detailed explanation of the calibration procedure.

[15]While there are no conceptual difficulties to including more sectors or stages of production, estimation of the model becomes computationally expensive as these dimensions increase. Specifically, the number of equations to be solved increases linearly with the number of sectors, but with the square of the number of production stages.

labor productivity in the durable sector. This specification for TFP allows for considerable flexibility. Including both transitory and permanent features to the process governing TFP addresses the observation by Gorodnichenko and Ng (2010) that constraining the model to only one component can materially affect estimation results.

We make use of four aggregate series in the estimation: output, consumption, hours, and inventories. Output is the sum of consumption, fixed investment, and changes in inventories. Our definition of output, therefore, excludes government consumption and net exports.[16] Separate data on fixed investment is redundant since it is spanned by the other time series. All variables are in terms of the working age non-institutionalized population, converted to natural logs, and enter in first differences. With the exception of hours data, all series are extracted from the Haver Analytics database. Series for output, consumption, and inventories are constructed using NIPA data produced by the Bureau of Economic Analysis. All variables are measured in real terms, and we aggregate price deflators using Divisia indices whenever appropriate. Inventories are taken directly from the NIPA data. Since we do not model durable consumption explicitly, consumption only includes nondurable goods and services. We also add to consumption the services produced by durable goods, calculated using the formula in the technical appendix of Chari, Kehoe, and McGrattan (2007). We treat durable consumption as part of fixed investment and, thus, part of output. Finally, hours data were calculated by the Bureau of Labor Statistics following the procedure in Francis and Ramey (2005). Our data series are quarterly and cover the period from 1953:Q3 to 2011:Q4.

We estimate the model using the Bayesian approach detailed in An and Schorfheide (2007). This requires choosing a prior distribution for the parameters to be estimated, which is then combined with the likelihood function for the linear rational expectations model laid out above. The joint density is evaluated using the Kalman-filter and the posterior distribution is computed using a random-walk Metropolis-Hastings algorithm with 500,000 draws. We assume that the prior distribution of the substitution elasticity ϱ is Gamma with a mean of 4 and a high variance. This assumes a reasonable amount of substitution between output produced in different periods, as would be the case in typical models of inventory investment. As for the shock processes, we assume that they follow an AR(1) process and adopt a Beta prior for the persistence parameters (denoted $\rho_u, \rho_g, \rho_{a_D}, \rho_\Upsilon$ and ρ_ζ with subscripts representing the corresponding margins being affected) with a mean of 0.9,

[16]This assumption may not be entirely innocuous. Alessandria, Kaboski, and Midrigan (2013) have argued that foreign trade and inventory dynamics interact in important ways over the business cycle.

except for the growth rate of the permanent component of TFP, and standard deviation 0.5. For the process governing the growth rate of the permanent component of TFP, we choose a lower prior mean of 0.5, and a larger standard deviation of 0.2.

We report the estimation results in Table 2. The posterior mean of ϱ is 18.9, which indicates that the data are informative with respect to this parameter. This implies a high degree of substitutability between stages of production. The estimated production function thus approximates a storage technology, while keeping a long-run target level for the inventory-sales ratio. In other words, the technology reproduces features similar to "stock-out avoidance" models of inventory behavior that combine a linear storage technology with a cost of deviating from a long-run target. The estimated shock processes are highly persistent with auto-correlations approaching unity, the exception being the shock process that captures the growth rate of the permanent component of TFP with a posterior mean for the autocorrelation coefficient of 0.66.

5 Empirical Findings

We now present the main contribution of the paper, namely the role that variations in different margins play in explaining post-war U.S. business cycles. In the spirit of the early RBC literature, we first attempt to gauge how well variations in technology alone can account for the changing nature of business cycles. Our key finding is that, while the effects of technology shocks are qualitatively in line with various comovement properties and relative volatilities of economic aggregates prior to 1984, including those pertaining to inventories, these shocks cannot account for shifts in business cycle patterns after 1984, even with the flexible production framework adopted here. Although fluctuations in technology still explain a large percentage of output variations after 1984, they are unable to account for the bulk of the variation in hours after that date and, therefore, changes in the behavior of labor productivity. We also contrast some of our benchmark findings with those that emerge in the more restricted canonical one-sector growth model to highlight the role of inventories. Ultimately, our analysis leads us to focus on variations in the discount rate, potentially related to credit market frictions, as a driving force underlying recent U.S. business cycles, rather than variations in the valuation of leisure often interpreted as reflecting labor market distortions.

5.1 Impulse Response Functions

We now examine how disturbances to the different components of technology and preferences give rise to different patterns of relative volatility and comovement between aggregate variables. In doing so, we provide insight into how changes in those patterns correspond to changes in the underlying determinants of business cycles. To guide our discussion, we report impulse response functions of key variables to preference and technology shocks in Figures 1 and 2. Because we are primarily interested in comovement and volatilities relative to output, rather than in absolute volatilities, we scale each shock such that the average response of GDP over 32 quarters is positive and equal to 1.

To gain insight into the changes characterizing U.S. business cycles outlined in section 2, we first note that changes in the cyclicality of labor productivity, and in the volatility of hours relative to output, are more likely associated with increases in the cyclical importance of variations in preferences rather than in technology. This is apparent in Figure 1 which depicts the responses of output, hours, and labor productivity to disturbances affecting different components of preferences and technology.

The panels on the left show the responses of output, hours, and labor productivity to technology shocks.[17] The transitory aggregate shock and sectoral shock have similar implications in that (i) both generate distinctly positive comovement between output, hours, and labor productivity, and (ii) both imply a smaller change in hours relative to output. While these features are qualitatively aligned with moments describing U.S. business cycles prior to 1984 in Table 1, none are consistent with post-1984 business cycle moments. A permanent change in aggregate TFP stands out by generating a slight hump-shaped response in output and labor productivity. It also generates a decline in hours on impact through a wealth effect. This implies a fairly short-lived negative comovement between labor productivity and hours, as well as between output and hours, following a pattern highlighted by Sims (2011).

The right-hand side panels illustrate the response of output, hours, and labor productivity to shocks that increases the discount factor (ζ_t), and that reduce the disutility of labor (Υ_t). Both kinds of shocks lead to an increase in labor supply by altering, in the first case, the value of leisure *between* periods, and in the second case, its value relative to consumption *within* each period. Moreover, these shocks similarly imply (i) negative comovement between labor productivity and hours, (ii) a larger response of hours relative to output on impact,

[17]While not readily apparent in the figures, the effects of transitory shocks eventually dissipate. The persistence of the impulse responses to transitory shocks arises from high estimated autocorrelation coefficients ρ_u and ρ_{a_D}, as shown in Table 2.

and (iii) negative comovement between labor productivity and output. The first two features qualitatively align with moments describing U.S. business cycles after 1984. In addition,the last feature can serve to countervail the procyclicality of labor productivity induced by productivity changes, thus potentially helping to explain post Great Moderation data.

Changes in the cyclicality of labor-productivity and the relative volatility of hours suggest an increased role for preference shocks relative to productivity shocks after 1984. However, since shocks to both the rate of time preference and the disutility of labor have similar implications for labor productivity and hours, we need additional moments to distinguish between the relative contribution of the two. As we will see, inventory moments can play a significant role in the identification of these factors.

Turning to the responses of inventories and the inventory-sales ratio relative to output in Figure 2, one observation stands out. Shocks to the discount rate induce a larger response of inventories relative to output than do other shocks, including shocks to the disutility of labor. Relatedly, shocks to the discount rate induce a procyclical inventory sales ratio in contrast to the other disturbances. The reason for the differences is twofold: (i) shocks to aggregate TFP and to the disutility of labor underlying the responses shown in Figure 2 are estimated to be fairly persistent, thus inducing little incentive for changes in inventories, and in contrast, (ii) shocks to the discount rate, by definition, directly alter intertemporal valuations and, therefore, are more apt to generate substantial inventory investment. It follows that while variations in both the discount rate and the disutility of labor may potentially account for the joint behavior of output, hours, and labor productivity after 1984, shocks to the discount rate are uniquely positioned to account for the change in the relative volatility and cyclicality of both inventories and the inventory-sales ratio after that date.

5.2 Decomposing Moments of U.S. Business Cycles

Table 3 shows the estimated cumulative effects of the different components of technology and preferences on moments of the data both prior to and after 1984. In particular, the table is constructed using the estimated historical time paths for those very components. Reading the table from left to right describes how comovement properties and relative volatilities of the data in Table 1 change as each additional component is taken into account. The first three columns of Table 3 contain the successive effects of the different drivers of technology.

Considering the transitory aggregate component alone, we find that temporary productivity shocks induce labor productivity movements that are strongly correlated with both output, at 0.99, and hours worked, at around 0.95. These disturbances also produce an inventory-sales ratio that comoves negatively with output as in the pre-1984 data. As indicated by the impulse response function depicted in Figure 2, the latter finding is consistent with the negative overall effect of temporary TFP shocks on the inventory-sales ratio. In addition, temporary changes in TFP produce an inventory series whose standard deviation relative to output closely matches the data at around 0.79 relative to 0.74. In summary, the benchmark model driven by aggregate transitory technology fluctuations is qualitatively consistent with all key comovement properties and relative volatilities of the data in Table 1 before 1984. However, for the very same reason, the technology fluctuations we estimate, by themselves, lose their explanatory power when the comovement properties and relative volatilities of the data shift dramatically after that date.

The second column of Table 3 shows the effects of shocks that affect the permanent component of technology fluctuations on moments of the data. This aspect of technology is emphasized by Sims (2011) as an important driving force behind business cycles. Permanent changes to productivity generate a fall in labor supply initially through a wealth effect, which reduces the positive comovement between labor productivity, hours, and output. We find, however, that the reduction in comovement is not enough to account for the changing nature of the business cycle. The third column of Table 3 shows how these moments change with the addition of sectoral considerations, which we associate with shifts in the production possibilities of the durable sector. These sector-specific variations lower the positive comovement between labor productivity and hours worked further.[18] Ultimately, however, the labor productivity puzzle remains as labor productivity continues to be strongly correlated with GDP both before and after 1984.

More generally, Table 3 demonstrates that changes in technology, while qualitatively aligned with the nature of economic fluctuations prior to 1984, are not enough to explain salient features of U.S. business cycles over the last three decades. Aside from comovement patterns, we note that technology shocks can explain a remarkable 98 percent of output variations and 67 percent of the variation in hours before 1984, but account for 80 percent of fluctuations in output and only 37 percent in hours worked after that date.

The observation that technology fluctuations cannot easily account for the post-1984 shift in cyclicality of labor productivity led some researchers to explore the role of forces that can distort labor markets. Consistent with this broader approach, variations in the valuation

[18]This insight relates to Garin, Pries, and Sims (2013), who emphasize the importance of reallocative shocks in explaining changes in the nature of economic fluctuations over the last three decades.

of leisure arising through Υ_t can in our model be alternatively interpreted as variations in a stochastic labor income tax or labor wedge. We discuss this point further in section 4 of the online appendix. Thus, the fourth column of Table 3 shows how the moments of the data change with the addition of variations in the valuation of leisure. Comovement of labor productivity with output does decrease considerably but, in contrast to the data, ultimately remains distinctly procyclical in both the pre-1984 and post-1984 samples. Similarly, in moving from column 3 to column 4, labor productivity comoves less with hours, especially before 1984, but not to the point of resolving the labor productivity puzzle after 1984.

These findings were suggested in our analysis of the impulse responses in Figure 1, where shocks driving the disutility of labor generated opposite responses of labor productivity and hours and thus reduced the procyclicality of the former. However, at the same time, in moving the comovement properties of labor productivity closer to the data, changes in the disutility of labor also move the moments of inventory behavior in a counterfactual direction. After 1984, the inventory-sales ratio in column 4 of Table 3 becomes even more countercyclical, while the standard deviation of inventories falls, instead of increasing markedly as in the data. Indeed, Figure 2 illustrates that a fall in the disutility of labor raises output but lowers the inventory-sales ratio, which is opposite of what is needed to explain the shift in inventory behavior after 1984.

The last column of Table 3 considers the effects of shocks shifting the discount rate, captured by ζ_t. They play a significant role in lowering the procyclicality of labor productivity after 1984. The correlation of labor productivity and output goes from 0.64 in the post-84 period to 0.13 when these fluctuations are taken into account. In the post-84 period, our estimated shocks to the discount rate also move the correlation between labor productivity and hours from positive into negative territory. This result is foreshadowed in Figure 2, which shows that a shock shifting the discount rate moves labor productivity and hours in opposite directions, similarly to variations in the disutility of labor. It is also notable that variations in the discount rate change the cyclicality of the inventory-sales ratio from being countercyclical to acyclical after 1984. At the same time, we see from the impulse response functions that a shock which reduces the discount rate also increases both output and the inventory-sales ratio, thus contributing to a decline in the countercyclicality of the inventory-sales ratio. In summary, the key finding is that shocks affecting the discount rate play a distinctly important role in explaining shifts in the nature of business cycles post-1984.

5.3 The Time Paths of Recent U.S. Recessions

Figure 3 shows the paths of output, hours, and inventories following the 1980, 1991, and 2007 recessions when driven by changes in technology, the disutility of labor, and the discount rate separately. Shocks to technology alone can explain virtually all of GDP movements following the 1980 recession. However, they are not enough to explain output variations in the 1991 recession and the latter phases of the Great Recession.[19] Moreover, whereas shocks to technology explain a fair share of movements in hours and inventories during the 1980 recession, they can only explain a much smaller portion of those movements in the 1991 and 2007 recessions.

The key difference between the 1991 and 2007 recessions lies in the relative roles of changes in the valuation of leisure and the discount rate. While during the 1991 recession fluctuations in the discount rate play an important role in delaying the recovery, especially with respect to inventories, changes affecting the value of leisure are more prominent overall as they explain virtually all of the fluctuations in hours. In contrast, during the 2007 recession fluctuations in the discount rate capture not only the largest part of output deviations from trend starting from mid-2009, but also a substantial fraction of hours deviations, as well as virtually all of the fall in inventories.

In order to compare our model with inventories to the benchmark set by Chari, Kehoe, and McGrattan (2007), Figure 4 shows the same historical decompositions but obtained from estimating the canonical one-sector growth model without stages of production (i.e., by imposing $N = 1$ and $S = 0$), while also ignoring inventory data.[20] In the general model, fluctuations in the discount rate arising through ζ_t satisfy the Euler equation for fixed investment in each sector j,

$$\mu_{j,t} = \beta\zeta_t E_t[(1-\delta)\mu_{j,t+1} + \lambda_{j,t+1}R_{j,t+1}], \tag{14}$$

where $\mu_{j,t}$ and $\lambda_{j,t}$ denote the Lagrange multipliers associated with, respectively, equations (5) and (9) and $R_{j,t}$ is the physical return to investment in sector j. In the one-sector model, $\mu_{j,t} = \lambda_{j,t}$ so that estimated variations in ζ_t coincide with the investment wedge defined in Chari, Kehoe, and McGrattan (2007).[21] Within the context of the prototypical one-sector

[19] The online appendix also shows time paths for the 2000 recession which shares with the 1991 and 2007 recessions a greater influence of the discount factor on GDP.

[20] Furthermore, as in Chari, Kehoe, and McGrattan (2007), the estimated one-sector model abstracts from sectoral shocks and disturbances to the growth rate of TFP.

[21] See section 8 of the online appendix for details.

growth framework, findings for the 1980 recession indeed share key features with their paper despite a different calibration and a longer sample period that includes the Great Recession. In particular, a significant portion of the decline in output is explained by shocks to TFP in all recessions, whereby changes to the value of leisure also play a substantive role, especially in the case of hours worked. However, for the 1991 and 2007 recessions, the decomposition of macroeconomic aggregates from the prototypical growth framework clearly differs from our model.

In the model with inventories, estimates of variations in the discount rate are disciplined by an Euler equation for the production of each stage-s goods in each sector j,

$$B_j \left[\frac{Z_{j,t|t}}{\omega_j(s)Y_{j,t}}\right]^{-\frac{1}{\varrho}} \lambda_{j,t} = \beta^s E_t \left[\left(\prod_{u=0}^{s-1} \zeta_{t+u}\right) B_j \left[\frac{Z_{j,t|t+s}}{\omega_j(s)Y_{j,t+s}}\right]^{-\frac{1}{\varrho}} \lambda_{j,t+s}\right] \tag{15}$$

Recall in equation (13) that the production of stage-s goods, $s > 0$, is tantamount to producing new inventories. Therefore, the set of Euler equations (15) also constitute optimality conditions for inventory investment. Because estimates of variations in the discount rate or, equivalently, the investment wedge have to be consistent with these additional equations related to inventory behavior, the investment wedge in our generalized model can differ substantially from that in the conventional one-sector model.

In the 1991 and 2007 recessions and their aftermath, our generalized model with inventories assigns less of a role to technology and the valuation of leisure and a distinctively greater role to changes in the discount rate. This difference between models is particularly evident during the Great Recession and its tepid recovery. During that period, the discount rate switches from being essentially irrelevant in the one-sector growth model to being a primary driver of aggregate deviations from trend in the larger model. Thus, our model with inventories differs from the model without by attributing a more significant role to discount rate shocks in driving and prolonging the effects of recent recessions.

While in the model that we estimate shocks are purely exogenous and can be exactly mapped into wedges by way of stochastic distortionary taxes, Christiano and Davis (2006), and Buera and Moll (2012), caution that these could be partially endogenous in richer models. In particular, distortions to particular markets may manifest themselves in wedges seemingly unrelated to those markets. For example, Buera and Moll (2012) provide examples in which shocks that intensify credit constraints can affect either TFP or the labor wedge, while leaving the investment wedge unaffected. Moreover, Christiano and Davis (2006) emphasize that changes in credit market frictions or other distortions may manifest themselves in multiple wedges at the same time, thus generating comovement across wedges. Consistent with the latter observation, a standard Bayesian comparison of our model with and without correlated shocks strongly favors the first specification in terms of the posterior odds ratio.

With these caveats in mind, we view our findings as providing an interpretation of the importance of various sources of disturbances driving business cycles and, therefore, some guidance towards the most promising areas for model extensions. This interpretation is necessarily approximate because a new model element may easily show up in more than one shock in the model. That said, we argue in the next section that our estimated variations in the discount rate, which are essential in accounting for the shift in post-1984 business cycle moments, correlate well with various independent measures of credit market frictions.

6 Variations in the Discount Rate in a Model with Inventories

This section demonstrates that our estimates of variations in the discount rate, which play a central role in explaining key shifts in U.S. business cycles post 1984, are robustly linked to various independent measures of financial tightness and distress. As such, and with the limitations indicated by Christiano and Davis (2006) and Buera and Moll (2012), this finding is suggestive of the potentially important role of credit market frictions in driving business cycles. In addition, given the importance of inventory behavior in identifying discount rate fluctuations, this section also provides evidence on the model's ability to match important inventory facts that are robust across countries as well as other additional moments of the data.

6.1 Variations in the Discount Rate and Credit Market Frictions

Business cycle models with credit market frictions, such as Carlstrom and Fuerst (1997) and Bernanke, Gertler, and Gilchrist (1999), can in principle give rise to an investment wedge.[22] This suggests that its behavior can be used to assess the relevance of credit market frictions. As discussed above, however, subsequent research, chiefly Buera and Moll (2012), showed that the mapping from credit frictions to an aggregate investment wedge was not necessarily

[22] This point has been made earlier by Caggese (2007), who links inventory dynamics to financial market frictions.

a feature of models with credit market imperfections. For that reason, we now assess the extent to which variations in the investment wedge implied by our model, equivalent to our estimated discount rate shock ζ_t, can be plausibly interpreted as an index of credit market imperfections by comparing its behavior with other available measures of credit market frictions.

To the extent that variations in our estimated investment wedge capture in part the same information as these other indicators, they provide an additional indicator of financial frictions. In particular, the investment wedge that we estimate presents two related features. First, it does not depend directly on the details of specific institutions to which more conventional measures of credit market frictions are typically tied. Here, wedges are determined by the joint behavior of aggregate quantities, including inventories, and provide a corroboration of previous research that highlights the role of financial frictions. Second, we can then use our estimated investment wedge to provide a model-consistent assessment of the potential effects of credit market imperfections on business cycles.

Table 4 shows the correlation between four measures of financing conditions and macroeconomic aggregates. Panel a) shows the correlations with the 4-quarter-lagged spread between Moody's index of bond yields for bonds rated "Baa" and Treasury Bonds, a measure that is used by Hall (2010) as an indicator of credit frictions.[23] A substantial literature documents that corporate bond spreads are highly correlated with future output, and recent empirical and theoretical work links those spreads to frictions affecting financial intermediaries rather than default probabilities alone.[24] Lagged values of the corporate bond spread reflect the notion, emphasized by Chari, Christiano, and Kehoe (2008), and Gilchrist and Zakrajsek (2011), that over the short run, firms tend to rely on unused revolving credit lines. Therefore, increases in bond spreads have their highest impact on the marginal cost of funds only after some time. Panel b) focuses on dividend payouts to business owners, as calculated by Jermann and Quadrini (2012). It depicts the correlations with the negative of those payouts, since higher payouts are associated with smaller credit market frictions. Panels c) and d) highlight correlations of aggregates with, respectively, financial shocks estimated by Jermann and Quadrini (2012), and the Federal Reserve senior loan officer survey of bank standards for commercial and industrial loans. The latter survey provides information on the

[23] Hall (2011) focuses on the spread between Baa rated bonds and 20-year Treasury bonds, whereas our data concerns the spread relative to 10-year Treasuries, since those are the longest maturity available throughout the whole sample period.

[24] For empirical evidence, see Gilchrist and Zakrajsek (2012) and Adrian, Moench, and Shin (2010a,b). For a theoretical treatment, see He and Krishnamurthy (2012, 2013)

net percentage of domestic banks tightening standards on loans to large and middle market firms, and is lagged four quarters owing to the fact that tightening standards affect the flow of new loans rather than the stock of existing credit lines.

Where the data is available over the full sample, Table 4 shows that the negative correlation of indicators of financial frictions with different macroeconomic aggregates becomes noticeably more pronounced over time, reaching their most negative values in the Great Recession period. Where data is only available after 1984, namely for the Jermann and Quadrini (2012) estimates of financial shocks and the Federal Reserve officer loan survey, the negative correlations of financial tightness with aggregates also become more pronounced during the Great Recession, reaching values in excess -0.8 in all but one case. In addition, panels a) and b) indicate that while the correlations between indicators of financial distress and output or fixed investment are relatively weak prior to 1984, the correlation with inventories is noticeably stronger. This provides further support for our empirical strategy that uses inventory data to help infer the investment wedge.

Figure 5, panel a), depicts cyclical variations in the investment wedge over time compared with the lagged Baa-Treasury bond spread. These variations not only correlate closely with this spread but, remarkably, the two series move over the same range. The comovement between the two series is especially evident after 1984, and the fact that this comovement increases over time is consistent with the notion that changes in financial markets have made bond spreads more informative measures of financial frictions. In particular, the period after 1984 has seen a significant deepening of bond markets along with a much broader range of firm participation in those markets. Panels b) and c) of Figure 5 illustrate the comovement between our estimated variations in the investment wedge and, respectively, Jermann and Quadrini's (2012) measure of financial distress and the Federal Reserve officer loan survey of credit standards. In both cases, as we also document in Table 5, positive comovement between the series is evident, especially so in the case of the Jermann and Quadrini (2012) measure.

As a measure of robustness, Table 5, panel a), shows the business-cycle frequency correlation of our estimated investment wedge with various alternative indicators of credit market conditions. With the exception of Debt Repurchases in the pre 1984 period, these business cycle correlations are always positive. Table 5, panel b), controls for the possibility that the different measures of credit market conditions share the same cyclical properties. It does so by depicting the partial correlations of the investment wedge with the various indicators of credit market conditions after extracting the common component that correlates with GDP. The resulting partial correlations are positive in all but one case.

In summary, the behavior of the investment wedge that emerges from our model informed by inventory behavior correlates well with a wide array of measures of credit market frictions. We take these observations as evidence that variations in the estimated discount rate shock capture distortions in credit markets to a reasonable degree. These conclusions do not hold for the simpler investment wedge computed using the one-sector growth model as suggested by the differences in behavior between these two wedges when comparing Figures 3 and 4.

6.2 The Stage-of-Production Framework as a Model of Inventories

The findings described above arise by way of a model that incorporates inventories through a stage-of-production framework. In particular, the framework serves two main purposes. First, it is general enough to nest various seminal models of production including the time-to-build technology of Kydland and Prescott (1982) and the input-output framework of Long and Plosser (1983). Second, the framework simultaneously shares key features of conventional inventory models extended to a general equilibrium setting. In this section, we make the case that the inventory behavior implied by our stage-of-production framework aligns well with key inventory facts compiled by Ramey and West (1999) and Wen (2005) for different advanced economies. While our estimation matches sample moments of U.S. data by construction, we explore the population properties of our model relative to a broader set of data on inventories at different frequencies as analyzed by Wen (2005). In this assessment, the model's ability to match moments at different frequencies is constrained by the dynamic properties of inventories implied by our stage-of-production technology. In turn, this technology hinges on a single parameter that cannot be identified from long-run averages, namely the elasticity of substitution between stages of production.

Table 6 compares population moments implied by our model with cross-country averages of various moments involving inventories. These averages are based on the moments reported in Tables 5 and 6 in Ramey and West (1999) and Table 1 in Wen (2005). Population moments are those that emerge asymptotically as the sample size approaches infinity. In our linearized framework, these may be obtained analytically from the state-space representation of the model. By construction, our model is estimated to jointly match the sample U.S. time-series for inventories and sales. However, as highlighted by Benati and Lubik (2014), and in line with our observations about the changing nature of business cycles, inventory facts tend to be unstable within the U.S. sample. Therefore, moments constructed to match finite post-war sample paths for inventories, output, and sales, do not approximate the long-run averages implied by the state space representation of the model. By exploiting data from various countries and pooling together their moments, one obtains improved estimates of the population moments describing inventory behavior.[25] The question then is: how do the population moments of the model compare with those that emerge from cross-country averages?

In reviewing work on inventories, Ramey and West (1999) ultimately emphasize two empirical regularities. The first is that inventory investment is procyclical or, equivalently, that output is more volatile than sales, which presented a challenge for early inventory models derived from a production smoothing motive. The second is that inventory movements are very persistent. Wen (2005) notices that the procyclicality of inventory investment is specific to business cycle frequencies. At higher frequencies, inventory investment becomes countercyclical. He further argues that these seemingly paradoxical features of inventory behavior at different frequencies present a litmus test for inventory theories in that they are not easily matched by standard inventory models. Interestingly, and consistent with Wen (2005), our model implies that inventory investment is unambiguously countercyclical at high frequencies and procyclical at business cycle frequencies (see Table 6).[26] Alternatively, the volatility of production relative to sales decreases noticeably in moving from business cycle frequencies to high frequencies. When both business cycle and higher frequencies are combined, our model implies that production is at least as volatile as sales, although admittedly falling short of the magnitudes in the data. This finding is robust to removing the low frequency component (i.e. the stochastic trend) in output and sales using alternative filtering procedures. Finally, with respect to Ramey and West's (1999) second empirical regularity of inventory behavior, Table 6 shows that our model indeed produces a very persistent inventory-sales ratio, in fact somewhat more so than suggested by the data.

One dimension that is left unexplored in our analysis concerns the possibility that secular changes in inventory management, brought about the information technology revolution over the last decades, could have played an important role in explaining the stylized facts in this paper. With improved information flows, it is conceivable that firms might react more

[25] This assumes a stationary data generating process in first differences where innovations are at most weakly correlated across countries.

[26] In that sense, our framework resembles Maccini, Moore, and Schaller (2015), who address the Wen (2005) facts by way of permanent sales shocks together with production smoothing and stock-out avoidance motives.

quickly to changes in the economic environment, consistent with higher relative inventory volatility and a less countercyclical inventory-sales ratio. In our model, this channel would imply greater substitution between stages of production. The emergence of those processes around the start of the Great Moderation has been highlighted by Kahn, McConnell, and Perez-Quiros (2002), Irvine and Schuh (2005), McCarthy and Zakrajsek (2007), and Davis and Kahn (2008) as a potentially important source of output stabilization in that period. Thus, we estimate our model over two separate subsamples split in 1984. We adjust calibrated parameters so that the model matches the average inventory-sales ratio in each of the subperiods, which stands at, respectively, 1.57 and 0.37 for durables and non-durables prior to 1984, and 1.32 and 0.35 for durables and non-durables after that date. Our findings indicate that ϱ actually decreases from around 19.74 to 16.39, with standard deviations of 0.15 and 0.24, respectively. Thus, to the extent that advances in information technology have led to an evolution in inventory management processes, the effects appear to have been most evident at low frequencies, as evidenced by the lower average inventory-sales ratio after 1984 relative to the pre-Great Moderation period.

7 Concluding Remarks

Until the early 1980s, conventional wisdom held that, in the words of Lucas (1977), "business cycles are all alike". This informed the development of real business cycle theories, which were highly successful in explaining business cycles along key dimensions. After 1984, however, business cycles changed. The volatility of output became smaller and the relative volatilities of labor input and inventories increased substantially, with labor productivity moving from pro-cyclical to counter-cyclical and the inventory-sales ratio from counter-cyclical to acyclical. We investigate which changes in the underlying mechanisms behind business fluctuations could have led to these changes. We find that these changing business cycle stylized facts align well with a changing role of financial factors.

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Table 1: **Changes in Business Cycle Properties in the Post-War Era**

	1953-1983	1984-2008	2008-2012
	a. Cross Correlations		
Output per Hour and Output	0.65	0.06	0.06
Output per Hour and Hours	0.13	-0.47	-0.33
Inventory/Sales and Output	-0.57	-0.03	0.18
	b. Standard Deviations		
Output	2.59	1.43	2.57
Consumption Relative to Output	0.37	0.44	0.37
Investment Relative to Output	2.04	2.35	2.52
Hours Relative to Output	0.77	1.12	1.04
Inventories to Output	0.75	1.13	1.22
Inventory-Sales Ratio to Output	0.87	0.71	0.67

Note: Correlations and Standard Deviations calculated from HP-Filtered data. See text for details of variable definitions.

Table 2: **Model Parameters**

	Posterior Mode	Posterior Std.	Prior Mean	Prior Std.	Prior Distribution
g	1.004	-	-	-	Calibrated
δ	0.025	-	-	-	Calibrated
κ	0.40	-	-	-	Calibrated
β	0.99	-	-	-	Calibrated
$\omega_D(s+1)/\omega_D(s)$	0.61	-	-	-	Calibrated
$\omega_{ND}(s+1)/\omega_{ND}(s)$	0.15	-	-	-	Calibrated
ϱ	18.91	0.4124	4	4	Gamma
ρ_u	0.9978	0.0028	0.9	0.05	Beta
ρ_g	0.6555	0.0535	0.5	0.20	Beta
ρ_{a_D}	0.9980	0.0027	0.9	0.05	Beta
ρ_Υ	0.9890	0.0045	0.9	0.05	Beta
ρ_ζ	0.9984	0.0026	0.9	0.05	Beta

Table 3: **Cumulative Effects Technology and Preference Shocks on Data Moments**

	TFP Transitory	TFP Permanent	TFP Sectoral	Labor Disutility	Discount Rate	Data
			a. corr(GDP, GDP/Hours)			
Pre 84	0.99	0.93	0.89	0.57	0.67	0.65
Post 84	0.99	0.98	0.87	0.66	0.13	0.13
			b. corr(Hours, GDP/Hours)			
Pre 84	0.96	0.74	0.51	0.27	0.16	0.14
Post 84	0.96	0.91	0.18	0.17	-0.38	-0.38
			c. corr(GDP, Inventories/Final Sales)			
Pre 84	-0.23	0.26	-0.26	-0.27	-0.61	-0.58
Post 84	-0.30	-0.13	-0.45	-0.50	0.08	0.01
			d. Std(GDP)			
Pre 84	2.27	2.49	2.57	3.33	2.62	2.61
Post 84	1.61	2.05	1.34	1.59	1.67	1.67
			e. Std(Hours)/Std(GDP)			
Pre 84	0.37	0.54	0.53	0.85	0.75	0.77
Post 84	0.37	0.43	0.50	0.76	1.07	1.07
			f. Std(Consumption)/Std(GDP)			
Pre 84	0.42	0.33	0.98	0.77	0.36	0.37
Post 84	0.42	0.36	1.34	1.21	0.41	0.41
			g. Std(Inventories)/Std(GDP)			
Pre 84	0.79	1.11	0.98	0.92	0.73	0.74
Post 84	0.77	0.87	0.86	0.78	1.13	1.15

Note Calculated based on HP-filtered time-series obtained from historical decompositions.

Table 4: **Cyclical Correlations of Credit Conditions and Macroeconomic Aggregates in the Post-War Era**

	1953-1983	1984-2007	2008-2012
	a. Bond Spread (Baa - 10 year Treas, Lagged)		
Output	-0.079	-0.380	-0.627
Fixed Investment	-0.091	-0.451	-0.704
Inventories	-0.607	-0.649	-0.841
	b. (-) Payouts to Business Owners (Total)		
Output	-0.119	-0.546	-0.781
Fixed Investment	-0.119	-0.528	-0.797
Inventories	-0.204	-0.553	-0.825
	c. Jermann and Quadrini's (2012) Financial Shock		
Output	-	-0.741	-0.968
Fixed Investment	-	-0.686	-0.934
Inventories	-	-0.709	-0.691
	d. % of Domestic Banks Tightening Standards (Lagged)		
Output	-	-0.662	-0.877
Fixed Investment	-	-0.700	-0.901
Inventories	-	-0.466	-0.833

Note: HP-Filtered Data

Table 5: **Business Cycle Correlation of Investment Wedge with Indicators of Credit Conditions**

	1953-1983	1984-2007	2008-2012
		a. Total Correlations	
Lagged Baa-Treasury Spread	0.493	0.636	0.837
Lagged Baa-Aaa Spread	0.368	0.376	0.779
Lagged Aaa-Treasury Spread	0.502	0.615	0.861
Lagged GZ Spread	-	0.534	0.792
Lagged GZ Excess Bond Premium	-	0.437	0.743
(-) Payouts (total)	0.106	0.489	0.799
(-) Payouts (corporate)	0.201	0.486	0.564
Debt Repurchases	-0.103	0.389	0.705
Jermann and Quadrini (2012)	-	0.500	0.633
% Banks Tightening Standards	-	0.293	0.794
		b. Partial Correlations	
Lagged Baa-Treasury Spread	0.548	0.589	0.809
Lagged Baa-Aaa Spread	0.473	0.267	0.719
Lagged Aaa-Treasury Spread	0.504	0.595	0.860
Lagged GZ Spread	-	0.409	0.754
Lagged GZ Excess Bond Premium	-	0.320	0.699
Payouts (total)	0.212	0.474	0.785
Payouts (corporate)	0.358	0.470	0.500
Debt Repurchases	0.185	0.345	0.726
Jermann and Quadrini (2012)		0.331	0.009
% Banks Tightening Standards		-0.188	0.606

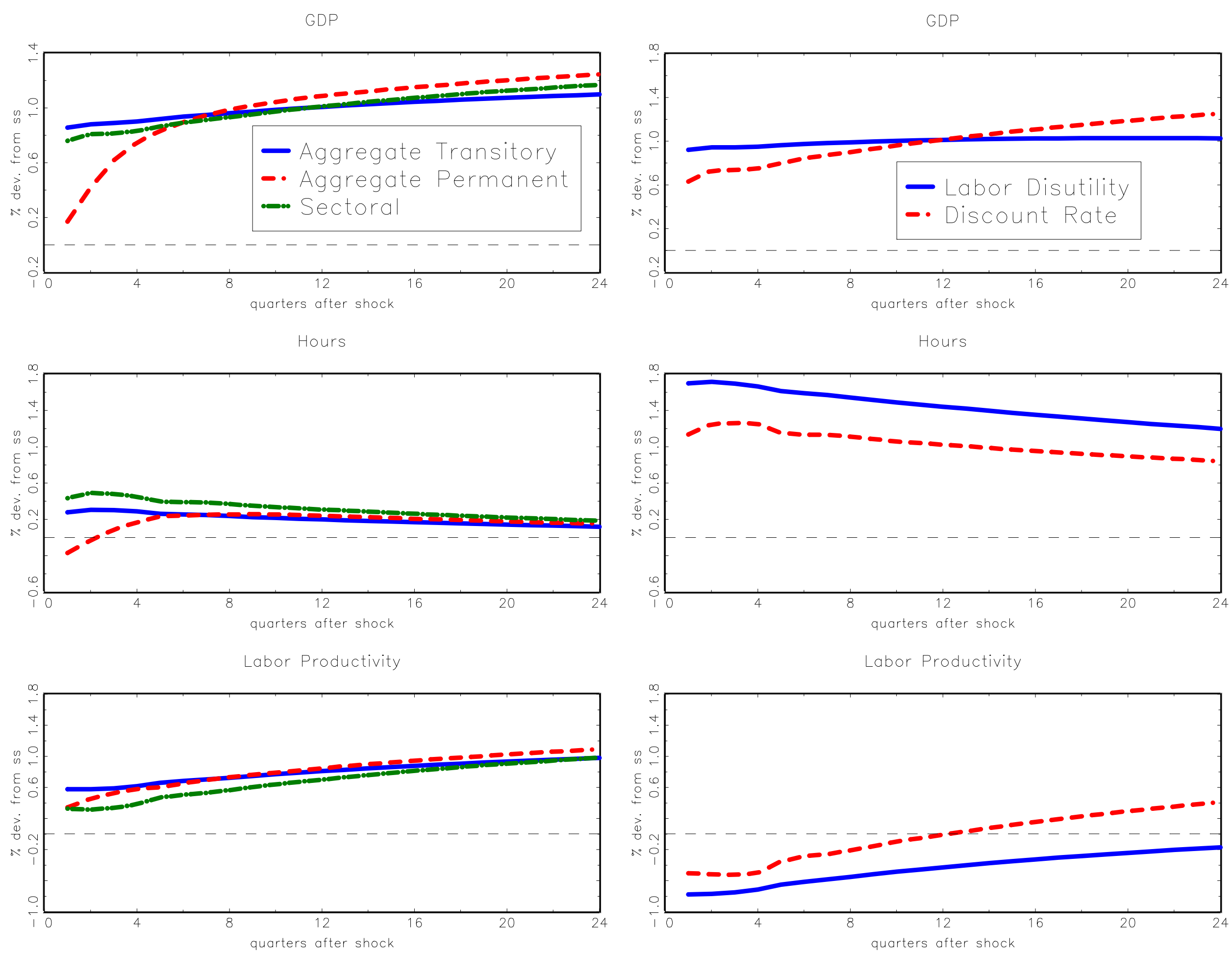
Note: HP-Filtered Data. % of Banks Tightening Standards refers to the net fraction of banks that reported having tightened lending standards of C&I loans to medium and large firms, from the Senior Loan Officer Opinion Survey on Bank Lending Practices performed by the Board of Governors of the Federal Reserve System. GZ Spreads are those calculated by Gilchrist and Zakrajsek (2012). Bond spreads and % of banks tightening standards are lagged four quarters.

Table 6: **Population Statistics and Cross-Country Averages**

	Model	Data
High frequency (2-3 quarters)		
$std(y)/std(s)^1$	0.57	0.89
$corr(s,i)^1$	-0.84	-0.45
Business cycle frequency (8-40 quarters)		
$std(y)/std(s)^1$	1.02	1.32
$corr(s,i))^1$	0.14	0.58
All frequencies		
$std(y)/std(s)$ (yearly, differenced)^2	1.01	1.49
$std(y)/std(s)$ (less unit root trend)^2	1.01	1.25
First auto-correlation x/s^3	0.99	0.93
Second auto-correlation x/s^3	0.98	0.85

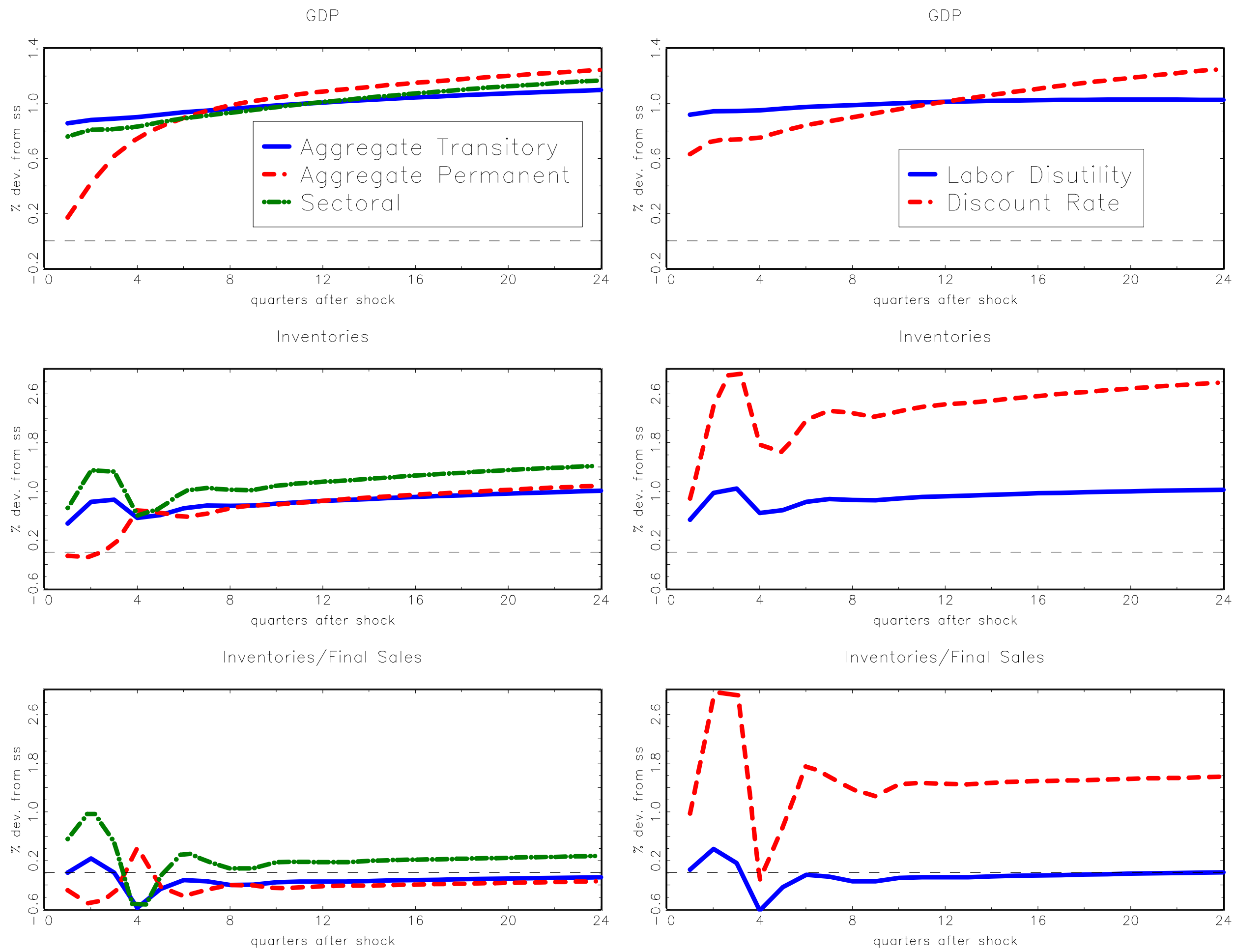
Note: y refers to output, s to sales, i to inventory investment, and x to the inventory stock. Model population statistics calculated from state-space representation of the model (see online appendix for details).
Data sources: (1) From Wen (2005), Table 1, values reported for OECD averages, (2) From Ramey and West (1999), Table 5, based on annual data, (3) From Ramey and West (1999), Table 6, based on annual data.

Figure 1: **Impulse Response Functions for Output, Hours and Labor**



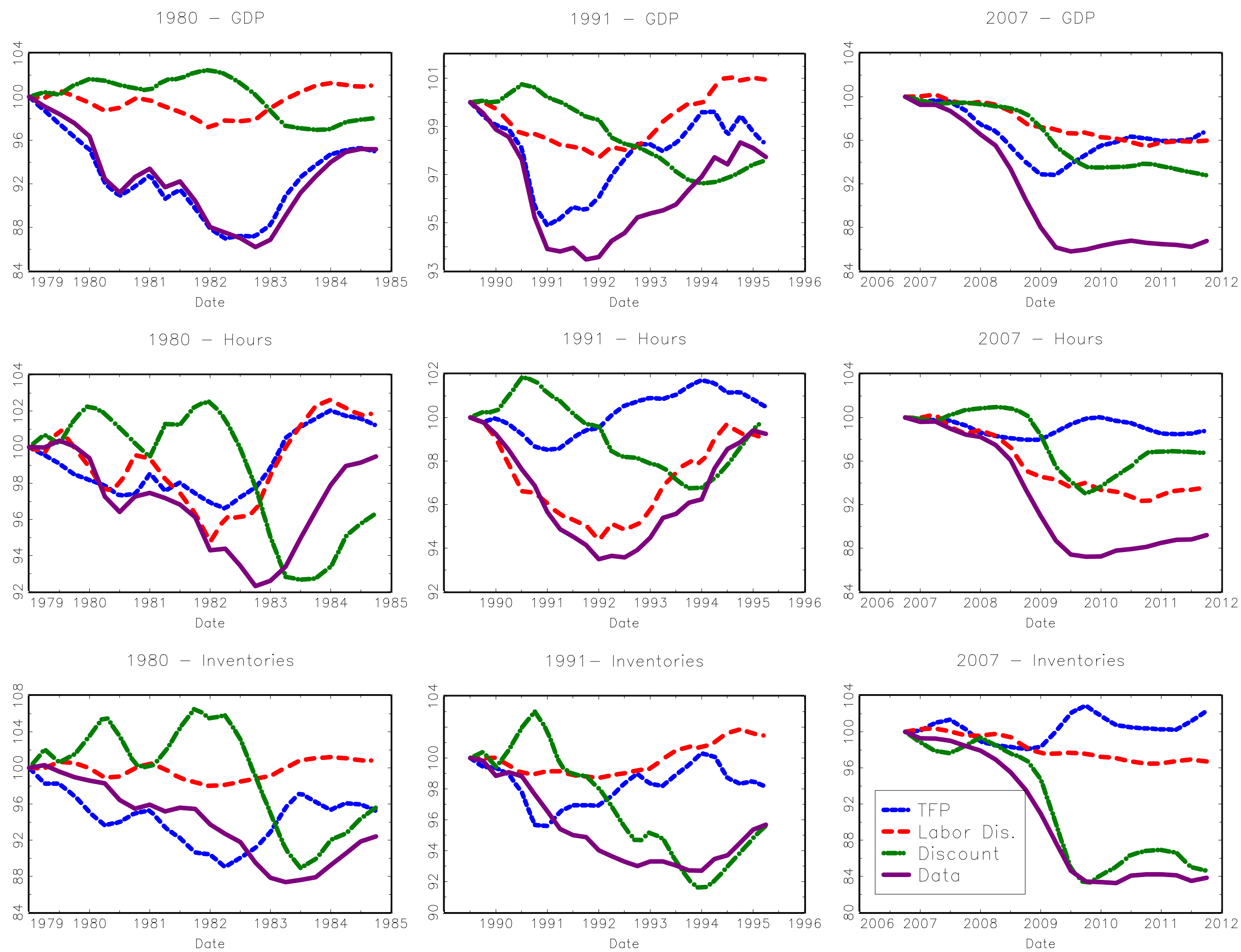
Note: Based on posterior mode estimate of model parameters.

Figure 2: **Impulse Response Functions for Output, Inventories and Inventory/Sales**



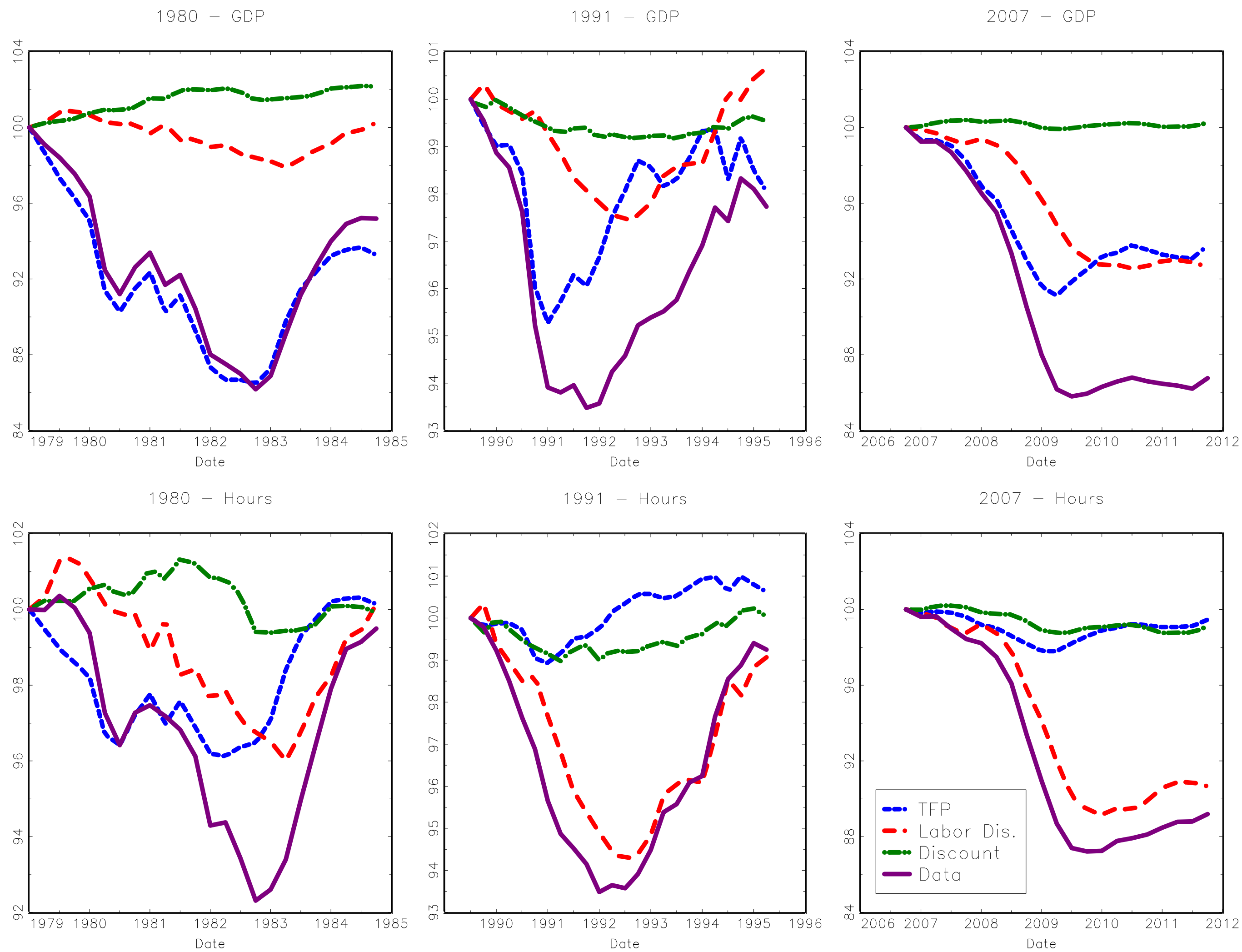
Note: Based on posterior mode estimate of model parameters.

Figure 3: **Historical Decomposition of Three Recessions - Benchmark**



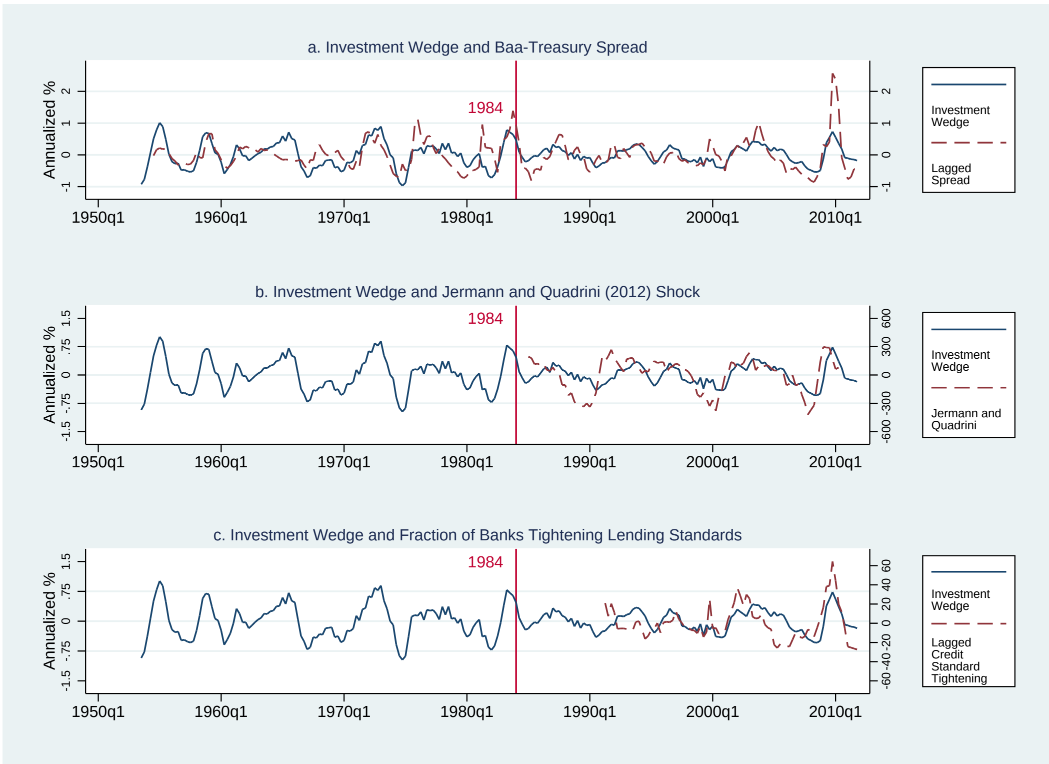
Note: Based on posterior mode estimate of model parameters.

Figure 4: **Historical Decomposition of Three Recessions - One Sector/Zero Stages of Production**



Note: Based on posterior mode estimate of model parameters for the model with $S = 0$ and $N = 1$ and using data for aggregate consumption, output and hours worked.

Figure 5: **External Validation and History of the Investment Wedge**



Note: Based on posterior mode estimate. Panel a) compares the estimated investment edge with the spread between and index of Moody's Baa rated corporate bonds and 10-year Treasuries. The spread is lagged four quarters. Panel b) shows the comparison with the financial shock estimated by Jermann and Quadrini (2012). Panel c) shows the comparison with the net fraction of banks that reported having tightened lending standards of C&I loans to medium and large firms, from the Senior Loan Officer Opinion Survey on Bank Lending Practices performed by the Board of Governors of the Federal Reserve System.