Firm Dynamic Choices and their Aggregate Implications

by

Alberto J Arredondo Chavez

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Doctoral Committee:

Professor Christopher House, Chair
Associate Professor Javier Cravino
Professor John Leahy
Assistant Professor Pablo Ottonello

Alberto J. Arredondo Chavez

aarredoc@umich.edu

ORCID iD: 0000-0001-6332-1299

To my parents

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ABSTRACT

The production decisions of the firm are important to understand aggregate economic fluctuations. The firm's dynamic choices, inventories or unfilled orders, hold valuable information about the firms intertemporal optimization problem that is relevant when studying the business cycle. In this research, I use aggregate and firm-level data on these variables, along with suitable theoretical frameworks, to study three different macroeconomic questions of current relevance.

Chapter I

Introduction

The producers' choices of inventories and unfilled orders contain valuable information on the firm's intertemporal problem. In many cases, the study of these choices allows us a clearer understanding of the mechanisms behind economic fluctuations. In this research, I use aggregate and firm-level data on these variables, along with suitable theoretical frameworks, to study three different macroeconomic questions of current relevance.

First, in Chapter II, I look at the effect of financing constraints of capital goods producers on aggregate investment. When a firm wishes to invest, it puts in an order with a capital goods producer. The latter manages the time to fulfill the order in order to maximize its profits. In times when this lag is big, there will be a gap between investment demand, the orders, and the actual change in the stock of productive capital. I show empirically that capital producers that face financing constraints take longer to deliver capital goods. Further, in downturns, when financing conditions are tighter, the average time to deliver is larger and increasing. Using a standard DSGE model augmented with the capital goods producer problem and working capital requirements, I find that this mechanism can substantially dampen the recovery of investment following a deep recession.

Second, in Chapter III (with Andrew D. Usher), we use data on the ratio final goods inventories to sales, in order to estimate changes in the price markup in the economy. There has been an important increase in market concentration in several industries in the last 5 decades. One way of finding whether this increase has also led to an increase in market power is to look at the change in the price markup in this period. The consensus in the literature is that firms hold inventories in order to facilitate sales. In this case the foregone value of missing a sale for having a low stock will be the price markup. This means that firms should choose to hold larger stocks in periods when the markup is high. Using this type of model, we find that the price markup has been relatively stable and may in fact have slightly decreased.

Finally, in Chapter IV, I study the relation between inventory and capital investment in an economy in which distribution technology has improved. With better distribution technology, firms can move from holding inventories to produce sales to hold them to smooth the costs of production. In the former case, inventory and capital investment are complements in the production of sales. In the latter they are substitutes. This change in the relation between inventories and capital investment leads to a reduction in the volatility of capital investment. This results shows promise to explain, at least partly, the recent behavior of capital investment.

Chapter II

Time to Deliver: Financing Constraints of Capital Goods Producers and Investment Dynamics

2.1 Introduction

Aggregate investment is one of the more volatile components of GDP and its dynamics are at the core of our understanding of business cycles. Recently, the literature has focused mostly on the investment problem of the investing firm and the households that provide their savings. In this paper, I take a look at the role that the capital goods producers play in determining investment dynamics. Most capital goods, as pointed out by *Belesley* (1969), are produced to order, creating a lag between the orders placed by an investing firm and the shipments realized by the capital goods producer. This delivery lag is captured by the ratio of unfilled orders to shipments. In capital goods production this ratio is very volatile, with a standard deviation about four times that of GDP, and it is countercyclical, with a correlation with GDP of -0.26[1]. These empirical facts suggest that it is not enough to look at the behavior

[1] The standard deviations and correlation between GDP and the ratio of unfilled orders to shipments are calculated from hp-filtered data of the natural log of GDP and the level of the ratio with a smoothing parameter of 1600. The data on unfilled orders and shipments comes from the M3 survey of the Census Bureau and corresponds to the aggregate series for Non-defense Capital Goods Excluding Aircraft. I describe the dataset further in the following sections and the data Appendix A

of investment by firms or savings by households in order to know by how much, delivered, installed and productive capital changes through the cycle. Simply put, the same amount of firm investment will not deliver the same change in the productive capital stock within the same number of periods throughout the cycle.

In this paper I tackle the question of the importance of this cyclical gap between new orders and shipments of capital goods[2] by first, gathering descriptive evidence on the behavior of shipments, new orders and unfilled orders throughout the cycle. In particular, I find that the countercyclicality of the unfilled orders to shipments ratio is mostly driven by state-dependent behavior of capital goods producers. When the economy is below trend, the elasticity of unfilled orders with respect to GDP is significantly smaller than when the economy is above trend. For shipments, the elasticity is higher when below trend. Putting these results together, we have that, as GDP falls, capital producers accumulate unfilled orders relative to shipments. This is consistent with findings in *Meier* (2018) who shows that the ratio of unfilled orders to shipments peaks during recessions and *Nalewaik and Pinto* (2014) who find that the response of capital goods shipments to new orders is stronger in periods when new orders are low.

To interpret the data, I use a theoretical framework in which capital producers manage shipments in order to smooth a convex cost of production. Aggregate series on new orders and shipments suggest this to be the case, as the volatility of shipments is about 0.65 times that of new orders. I show that, although this cost smoothing framework does a good job at matching different moments of the data on shipments, new orders and unfilled orders, it is incapable of generating a countercyclical unfilled orders to shipments ratio.

Augmenting the cost smoothing framework with a financing friction helps ratio-

[2]Investment in machinery and equipment accounts for roughly half of aggregate investment according to the National Income and Product Accounts. I do not consider structures in this paper but how this two types of capital are allocated through the cycle is part of my ongoing research

nalize the countercyclical unfilled orders to shipments ratio. In the model firms must borrow to raise working capital in order to pay a fraction of production costs up front. The producer is able to pledge the unfilled orders as collateral in order to reduce the cost of borrowing[3]. In periods when new orders are low, the cost of borrowing is higher, this decreases the optimal level of shipments by both increasing the cost of production and creating incentives for the producer to hold unfilled orders to maintain its ability to borrow. It is important to mention that even without the use of unfilled orders as collateral, a producer that has to borrow to raise working capital will face a higher cost of production during a downturn when credit conditions are tighter.

I test the role of financing frictions by using variation in tax incentives as proxy for exogenous changes in new orders of capital goods and firm-level balance sheet data. In my main specification I find that the semi-elasticity of shipments to the tax incentive can be more than half a percentage point lower for financially constrained firms compared to their unconstrained counterparts. The opposite is true of the semi-elasticity of unfilled orders. These results are consistent with those for the aggregate elasticities with respect to GDP when the economy is above and below trend, providing validation for the financing friction as the relevant mechanism.

Finally, I embed the capital goods producer problem, including the financing friction, into an otherwise standard RBC model with real shocks to productivity in the production of consumption goods. I assume that the capital producer gets part of the payment for the new orders up-front and only has to borrow when this payment is less than the amount of working capital needed. This produces an occasionally binding constraint framework in which the capital producer only has to borrow in

[3]In the quantitative model of Section 2.6 unfilled orders have value as assets as they represent producers work-in-process. Alternatively, we can think of the portion of orders that is backed by an entry in Accounts Receivable, which can be traded as an asset. In Section 2.5 I provide evidence that the value of unfilled orders is related with lower borrowing costs

periods when new orders are low, matching the state-dependence behavior in the data. I use the algorithm of *Guerrieri and Iacoviello* (2017)[4] to produce a piecewise-linear approximation to the model around a steady state that preserves the non-linearity of the occasionally-binding constraint. The model produces hump-shaped asymmetric responses of investment. Following a positive innovation to productivity that increases GDP to a peak of one standard deviation, roughly 2%, the cumulative response of investment is 9.7% smaller than the response to an equivalent negative shock. The asymmetry in the response becomes stronger for bigger shocks. Following a fall in GDP of 4.3%, roughly the fall in the Great Recession, the cumulative fall in investment in the financial friction model is 67% larger than the response produced by a standard RBC model. The peak response is of similar magnitude across the two models however, the tail of the response in the financial friction model is fatter and longer. The hump-shaped dynamics in the financial friction model imply that bigger negative shocks produce slower recoveries. After the Great Recession shock it takes 16 quarters for the investment response in the financial friction model to catch-up with the response in the standard RBC model.

Related literature

This paper contributes to five strands of literature. First is the large body of research that studies how frictions shape the responses of aggregate investment[5]. I contribute to this literature by studying the importance of frictions in capital goods production and arriving to a mechanism that produces hump-shaped responses and investment slumps. Notably, since *Christiano et al.* (2005), adjustment costs of in-

[4]I make use of the tools discussed in *Guerrieri and Iacoviello* (2015)

[5]This includes work on (1) Lumpy investment: *Khan and Thomas* (2008), *House* (2014), *Winberry* (2018), *Caballero and Engel* (1999) and *Bachmann et al.* (2013), (2) Irreversibility: *Bertola and Caballero* (1994), *Abel and Eberly* (1996) and *Veracierto* (2002), (3) Capital specificity: *Altig et al.* (2011) and (4) financial frictions: *Bernanke and Gertler* (1989), *Carlstrom and Fuerst* (1997) and *Kiyotaki and Moore* (1997) among others.

vestment have been prominently featured in dynamic models in order to match the responses of investment. In related work *Fiori* (2012) provides a micro-founded explanation for hump-shaped responses of investment in a model of lumpy investment in both capital and consumption-goods production. Recently, *Ottonello* (2018) shows that accounting for capital unemployment in a search framework can rationalize both the hump-shaped responses of investment and investment slumps.

Second, the literature that studies the dynamics of capital goods production and their delivery lag. Some seminal work is that of *Maccini* (1973) and *Zarnowitz* (1962). Related to this paper, *Nalewaik and Pinto* (2014) show empirically that shipments of capital goods are more responsive to new orders in periods when new orders are low, a fact that hints at the countercyclicality of the delivery lag. In another related study, *Meier* (2018) interprets the delivery lag as time-to-build capital goods and cites this as evidence to back a framework in which supply-chain disruptions lead to contractions. I make a contribution by providing evidence that financing frictions are partly responsible for the behavior of shipments observed by *Nalewaik and Pinto* (2014) and the countercyclical delivery lag. To my knowledge I provide the first quantitative DSGE model with an endogenous delivery lag that arises from producers choices.[6].

Third, the literature that studies the importance of heterogeneity in financial conditions for aggregate investment fluctuations. Here we have the work of *Khan and Thomas* (2008) and *Gilchrist et al.* (2014) who study the effect of financial frictions faced by the investing firm in flexible price environments. In recent work *Ottonello and Winberry* (2019) show the importance of financial heterogeneity for the investment channel of monetary policy. They find that financially constrained firms invest less than their unconstrained counterparts, giving rise to state-dependence in the response

[6] *Kahn and Maccini* (2015) use the stages of production framework of *Sarte et al.* (2015) to build a partial equilibrium model that shows promise for taking it to general equilibrium.

of aggregate investment to monetary policy. The bulk of this literature focuses on financial frictions affecting the investing firm. The main distinguishing factor of my work is looking at role of financial frictions for aggregate investment through the problem of the capital goods producer. Similar to *Ottonello and Winberry* (2019), I find that financial frictions lead to state-dependency, in this case of the response of shipment of capital goods to shocks that generate new orders.

Finally, I make a small contribution to the ongoing research on the effects of tax incentives on aggregate investment. My empirical specifications make use of the comprehensive tax subsidy described in *House and Shapiro* (2008)[7]. They exploit variation from bonus depreciation and their theoretical intuition on the shape of investment demand, to estimate an elasticity of investment supply between 6 and 14 percent. Recently *Zwick and Mahon* (2017) exploit variation from two rounds of bonus depreciation, together with rich firm-level data on equipment purchases, to study heterogeneity in the responses of firms to this type of stimuli. They find that a one percent change in stimulus leads to an increase in equipment purchases of about 14 percent, smaller firms present a stronger response and firms react more to the policy when it generates cash flows. Finally, *House et al.* (2017) use the comprehensive tax subsidy to study the effect of stimulus on capital production. They find that a one percent increase in the stimulus raises purchases of capital goods by around 2 percent, half of which corresponds to equipment imports. I contribute by estimating the effect of tax incentives on shipments of capital goods. For the period spanning the life of the Investment Tax Credit, I find that a one percent increase in the tax subsidy leads to about 3 percent increase in capital goods shipments. I also find evidence that financing constraints dampen this response as constrained producers have a weaker response to the stimulus.

Roadmap

[7] See also the work of *Goolsbee* (1998)

This paper is organized as follows. In Section 2.2 I discuss some characteristics of capital goods producers that are relevant for the analysis. In Section 2.3 I show evidence of the countercyclical behavior of the unfilled orders to shipments ratio and the state-dependency of unfilled orders and shipments. In Section 2.4 I provide a theoretical framework to explain the findings through financing frictions while in Section 2.5 I provide evidence of the effect of those frictions. In Section 2.6 I build and calibrate a quantitative general equilibrium model which I use in Section 2.7 to derive implications for aggregate investment. Section 2.8 presents concluding remarks.

2.2 Characteristics of capital goods production

In this section I describe three characteristics of capital goods producers that will play an important role when analyzing their behavior in later sections. Capital producers produce mainly to order, they actively manage their production schedule and they do so in order to smooth the costs of production.

Production to order

Unfilled orders are a commitment to a future purchase/shipment. Unfilled orders and final good inventories tell us something about the production scheme of a manufacturer. Firms can be classified as

1. Production to order: the manufacturer receives a new order and manages production/delivery to maximize profits. This system of production arises when the produced goods require a certain degree of specificity or when it is not possible to forecast demand to hold a stock for sale. Firms that produce to order hold higher shares of unfilled orders and lower shares of final good inventories. This type of production seems natural for capital goods as machinery and equipment often require customization.

2. Production to stock: the manufacturer produces to hold a stock of final good

inventories according to expected demand. Unfilled orders arise from stock-outs. These producers hold a lower share of unfilled orders an higher share of final good inventories.

An important share of manufacturing firms hold unfilled orders. From the manufacturing firms in Compustat[8] 96.7% hold unfilled orders. Only 1.5% of capital goods producers have zero unfilled orders while the share goes to 5.5% for other manufacturers. Table (2.1) gathers statistics of the shares of unfilled orders and final good inventories for both capital goods producers and other manufacturers. In general, capital goods producers keep a larger share of unfilled orders than other manufacturers. The percentage of capital goods producers with at least two quarters[9] of unfilled orders is above 23% while it is 16% for other manufacturers. The opposite is true for final good inventories, in general capital goods producers hold a smaller share of them than other manufacturers. Above 67% of the capital goods producers hold more than twice the value of their final good inventories as unfilled orders. The number for other manufacturers is 55%.

Figure (2.1) shows the ratios of unfilled orders to shipments[10] and final good inventories to shipments for manufacturers within the categories of "Consumer Durables" and "Industrial Equipment Manufacturing"[11]. In panel (a), producers of consumer

[8] I give full descriptions of the data used at firm, sector and aggregate levels in Appendix A

[9] Meaning that the value of their unfilled orders is larger than twice the value of their quarterly shipments

[10] All references to shipments in Compustat data refer to the value of sales. One caveat of my firm-level analysis is that the order backlog, used as unfilled orders, may contain sales backlog as well as unfunded backlog. Making sales bigger than shipments. *Meier* (2018) compares the aggregate unfilled orders to shipments ratio computed using these Compustat variables to the the ratio from the M3 survey and finds them to be similar. This attenuates the concern of sales being different from shipments.

[11] Consumer durables include all manufacturers with 4 digit NAICS codes 3352 and 3371. Industrial equipment manufacturing includes producers within the 3332 NAICS code category.

Table 2.1: Ratios of unfilled orders and final good inventories to shipments

	$UFO = 0$	$\frac{UFO^{end}}{Ship} \geq 2$	$\frac{UFO^{end}}{FGI} \geq 2$
Capital goods	1.5%	23%	67%
Other manufacturing	5.5%	17%	56%
Total	3.3%	20%	63%

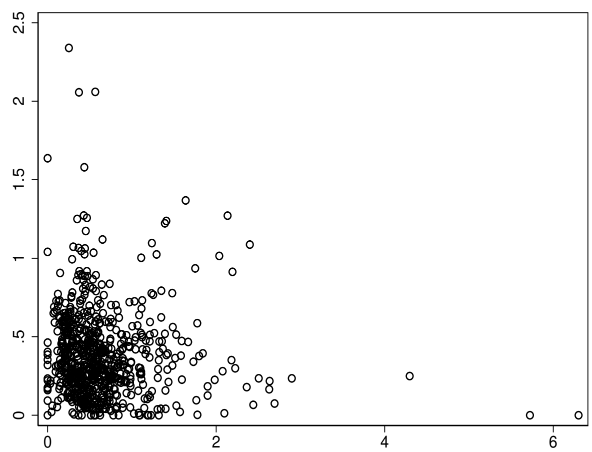
Notes:UFO represents the value of the order backlog at the end of the year. Ship is the value of annual sales divided by four. FGI are final good inventories at the end of the year. The classification into "Capital Goods" is done through NAICS codes according to BEA categories for private investment by type. Data is annual for the period between 1974 and 2018. All variables are taken from Compustat and converted to real terms. Description of the breakdown in categories and deflators used is given in Appendix A

durables have mainly low unfilled orders with most of them bunched under a ratio of 1. Their ratio of final good inventories to shipments mostly spans the range between zero and 1. In panel (b) for industrial equipment producers, the ratio of unfilled orders is much higher, spanning the range from zero to 4 while the share of final good inventories looks a little lower than that of the consumer durables manufacturers. These are the patterns discussed for a production to stock sector, Consumer Durables and a production to order one, Industrial Equipment.

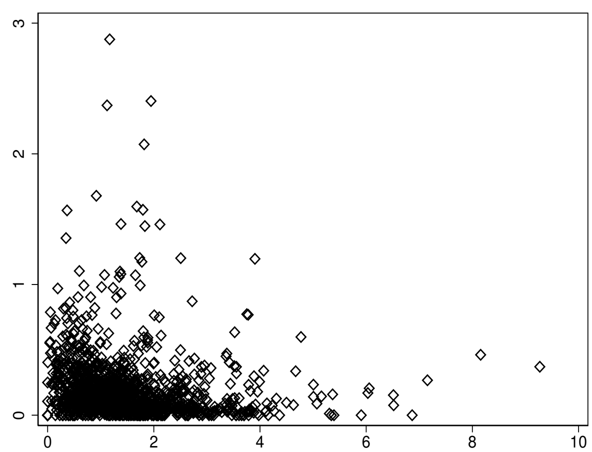
Figure (2.3) shows a the correlation between several lags and leads of the unfilled orders to shipments ratio and contemporaneous GDP in a correlogram. In panel (a) the ratio for consumer durables has a strong contemporaneous correlation with GDP. This reflect stock-outs in periods of high demand, when the producer runs-out the available inventory and takes in new orders. In panel (b), Capital Goods do not present the same correlation pattern from the "production to stock scheme". Instead we see an S-shaped curve in which the ratio of unfilled orders to shipments lags the cycle considerably. Further, the ratio is countercyclical contemporaneously. I will explain the lagged pattern in the correlation below as evidence that the capital goods producers use unfilled orders to smooth the cost of production. The countercyclicality

Figure 2.1: Unfilled orders (x-axis) vs Final good inventories (y-axis), ratios to shipments

(a) Consumer durables



(b) Industrial machinery

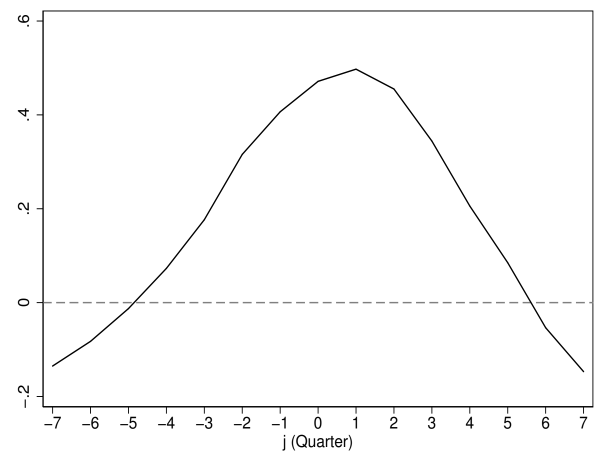


Notes: Each point on the scatter-plots represents the ratio for a firm-year pair for the period between 1974 and 2018. Ratios calculated from Compustat data deflated as discussed in Appendix A. The ratios of unfilled orders to shipments are trimmed at the 1st and 99th percentiles of all firms. The industries included in each of these categories are as discussed on the footnote.

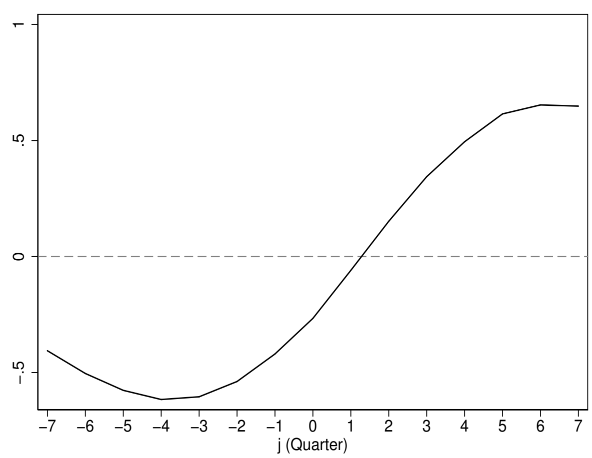
of the ratio is addressed in Section 2.4 when I introduce financial frictions.

Figure 2.2: Correlation between the $\frac{UFO^{end}}{Ship}$ in $t+j$ and the cyclical component of GDP in t

(a) Consumer durables



(b) Capital goods



Notes: Correlation between HP-filtered log-GDP and 7 leads and lags of HP-filtered ratio of unfilled orders to shipments. The smoothing parameter is 1600. All variables are in real terms.

Production schedule

The ratio of unfilled orders to shipments is volatile and cyclical. An important share of this variability comes from within firm variation, meaning that capital goods producers change their production schedule through time. The adjusted R-square of a firm-level and year-level fixed effects model on the capital producers unfilled orders to shipments ratio is 64%. This is the share of the variation in the ratio that is explained by variation across firms. The remaining 36% comes from variation captured by firm-time level observables or unobservables. This is the share of the variation in ratio that is attributable to changes from the capital goods producer problem through the cycle.[12]

Cost smoothing

The accounting relation between unfilled orders at the end of the period UFO, new orders NO and shipments $Ship$ is given by

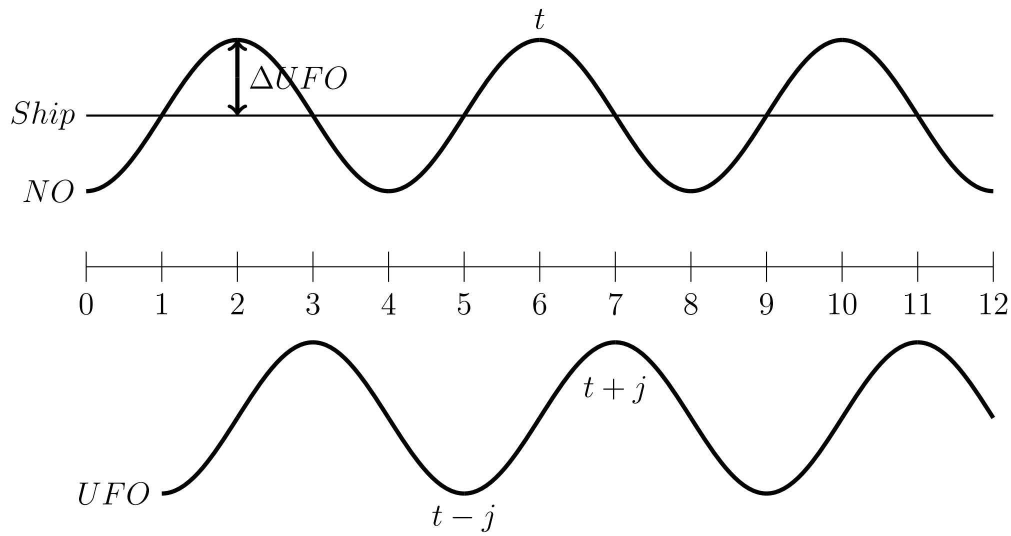
$$\Delta UFO_t = NO_t - Ship_t \tag{2.1}$$

Consider this thought experiment. A producer smooths the costs of production given the deterministic process for new orders shown by the top graph of Figure (2.3). Optimally, the producer sets constant shipments, shown by the straight line. Using equation (2.1) we can trace the unfilled orders curve as shown at the bottom of figure (2.3). This is the same wave as new orders lagged by a period. The correlation between new orders at time t and leads and lags of unfilled orders will be the highest at $t+j$ and lowest and negative at $t-j$ will have the lowest and negative correlation with NO_t. For the periods between $t-j$ and $t+j$ the S-shape of unfilled orders implies that the correlogram will between NO and UFO will be S-shaped, just like that in panel (b) of Figure (2.3). Shipments are constant, so this is also the correlogram between NO and the unfilled orders to shipments ratio. From this thought experiment, I conclude that the S-pattern correlogram in Figure (2.3) can be explained by the capital producers using unfilled orders in order to smooth the costs of production.

Now, from equation (2.1) if follows that unfilled orders smooth out shipments

[12] I find some evidence of cyclical composition effects in Compustat. These explain part of the 64% of across firm variation. I am currently studying this subject in the scope of a separate project but provide a short description of the composition evidence in Appendix A.

Figure 2.3: Cost smoothing under deterministic new orders



Notes: Thought experiment: new orders are assumed deterministic and follow a sinusoidal wave. Optimally, the producer chooses a constant level of shipments and the resulting unfilled orders follow a sinusoidal wave shifted by one quarter of the cycle of the wave.

relative to new orders if ΔUFO is procyclical. Figure (2.4) shows on panel (a) the time series of the cyclical components of shipments and new orders. Shipments are smoother than new orders. They are below new orders when new orders peak and above them when new orders fall. Panel (b) shows the cyclical component of ΔUFO along with recession bars. The series is procyclical giving evidence of cost smoothing in capital production.

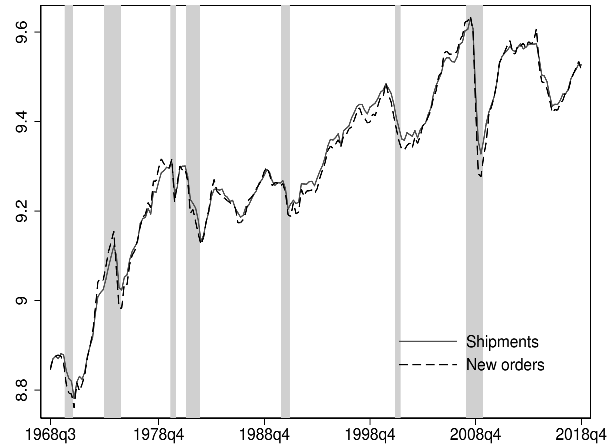
2.3 New orders, unfilled orders and shipments through the cycle

Descriptive analysis

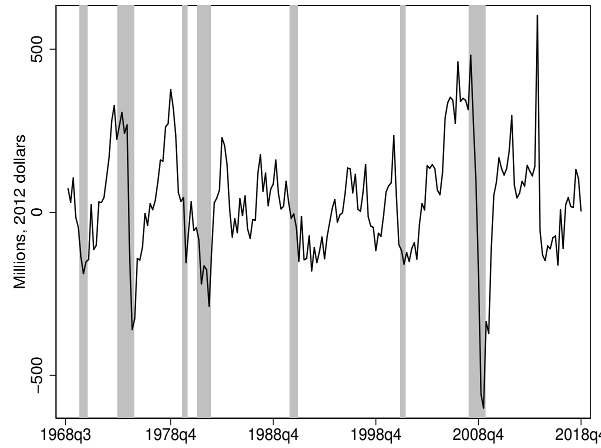
Three components determine the behavior of aggregate investment from the perspective of capital goods production: new orders, unfilled orders and shipments. Table

Figure 2.4: Cyclicality of shipments and orders

(a) Shipments and orders



(b) Change in unfilled orders



Notes: panel (a): Cyclical component of shipments and new orders of capital goods obtain with an HP-filter of the variables in logs, with smoothing parameter 1600. panel (b) Period-on-period change in the value of unfilled orders. All data is in real terms and corresponds to the category "Non-defense equipment excluding aircraft" from the M3 survey

(2.2) presents statistics of these variables in the business cycle. As aggregate investment, the three variables are procyclical, persistent and volatile, with standard deviations more than three times that of GDP. Notably, the correlation with GDP is lower than that of aggregate investment[13] for all the variables. The fourth column of the table presents the statistics for the ratio of unfilled orders to shipments. The ratio is countercyclical, with a correlation with GDP of -0.26, persistent and volatile.

Figure (2.5) shows on panel (a) the hp-filtered ratio of unfilled orders to shipments alongside the cyclical component of GDP for the period between 1968 and 2018. Consistent with the correlogram of Figure (2.5) the ratio seems to lag the cycle by about 5 to 6 periods. Panel (b) shows the ratio in levels for the same period. It presents a steep downward trend from the late seventies to the late nineties, a decline

[13]The correlation between aggregate investment and GDP for the post-war period is $Corr(GDP, I) = 0.83$ according to data from the NIPA tables

Table 2.2: Components of investment through the cycle

	NO_t	$Ship_t$	UFO_t	$\frac{UFO_t}{Ship_t}$
$corr(x, GDP)$	0.76	0.66	0.36	-0.26
$corr(x_t, x_{t-1})$	0.80	0.91	0.94	0.91
$\frac{\sigma_x}{\sigma_{GDP}}$	5.64	3.69	5.03	4.13

Notes: Computed from deflated M3 survey data for the category of "Non-defense equipment excluding aircraft"

that coincides with the introduction of "just in time manufacturing" to the west. The cyclical behavior of the ratio is obscured by the strong trend however, it is noticeable that it increases at the end of expansions and peaks well into recessions[14].

To explore this feature of the ratio, I compute correlations and elasticities of the variables, conditioning on whether the economy is above or below its trend[15]. The results, on Table (2.3) show some evidence of state-dependence, particularly for unfilled orders and their ratio with respect to shipments. The elasticity of the former with respect to GDP is almost three times bigger when the economy is above trend than when it is below. Similarly, the correlation of unfilled orders with GDP is higher above trend by the same factor of three. The ratio of unfilled orders to shipments turns to be almost acyclical when the economy is above trend and countercyclical when the economy is below. The elasticity of shipments with respect to GDP is slightly higher when below trend but not by a factor comparable to the state-dependence of unfilled orders.

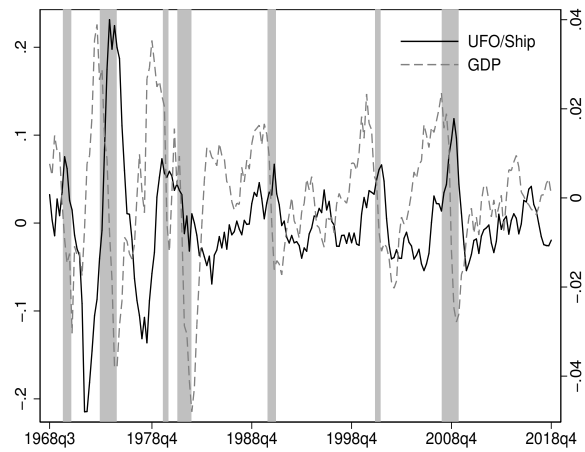
In summary, capital goods producers manage unfilled orders in order to smooth the cost of production. The resulting delivery lag is captured by an unfilled orders to shipments ratio that is countercyclical. This feature of the delivery lag appears to be driven by the behavior of unfilled orders and, to an extent, shipments during periods

[14] With the exception of the second part of the double-dip recession in 1981.

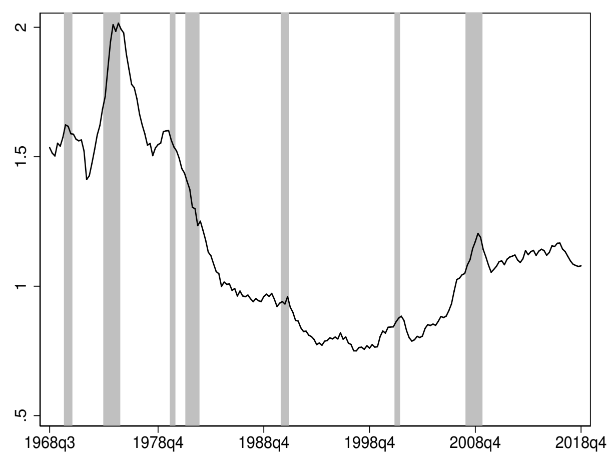
[15] I consider the economy to be below trend if HP-filtered log-GDP is negative. Positive values indicate the economy is above trend

Figure 2.5: The unfilled orders to shipments ratio through the cycle

(a) HP-detrended UFO/Ship ratio and GDP



(b) Ratio of unfilled orders to shipments in levels



Notes:panel(a): HP-filtered ratio of unfilled orders over shipments for "Non-defense equipment excluding aircraft" from the M3 survey and HP-filtered log-GDP from NIPA tables. Panel (b) Levels of the ratio of unfilled orders to shipments of the above mentioned data. Recession bands correspond to the NBER recession classification

Table 2.3: State-dependent elasticities with respect to GDP

	NO_t		$Ship_t$		UFO_t		$\frac{UFO_t}{Ship_t}$	
	Above	Below	Above	Below	Above	Below	Above	Below
$corr(x, GDP)$	0.58	0.66	0.41	0.42	0.25	0.08	-0.05	-0.34
$\frac{\partial ln(x_t)}{\partial ln(GDP_t)}$	2.93	3.85	1.74	2.5	3.01	1.19	-0.57	-1.95

Notes: Measures of above and below trend correspond to the sign of HP-filtered log-GDP. For new orders, shipments and unfilled orders calculations are done on HP-filtered log-values. Calculations with the ratio are done with HP-filtered levels. All variables correspond to "Non-defense equipment excluding aircraft" from the M3 survey

when the economy is below trend.

Theoretical analysis

Lets analyze the descriptive results using a cost-smoothing framework. Consider the problem of a producer of capital goods that faces a convex cost of production. Each period, the producer takes as given the market price P_t and new orders for capital goods $NO_t = NO(P_t)$ which go into the stock of unfilled orders according to

$$UFO_t^b = UFO_{t-1}^b - Ship_{t-1} + NO_t \tag{2.2}$$

$$UFO_t = UFO_t^b - Ship_t \tag{2.3}$$

The stock UFO^b corresponds to the unfilled orders at the beginning of the period, before production and shipments. It differs from the data object of the descriptive analysis, unfilled orders at the end of the period UFO_t. These two are related through equation 2.3. The producer chooses a level of shipments $Ship_t$ at a cost $C(Ship_t)$, $\frac{\partial^2 C(Ship)}{\partial Ship^2} \geq 0$ and receives per unit payment of P_t. Shipments in the period are constrained by the stock of unfilled orders.

$$Ship_t \leq UFO_t^b \tag{2.4}$$

The producers problem satisfies the Bellman equation

$$V(UFO, P) = \max_{\substack{UFO' \\ Ship \leq UFO^b}} \left\{PShip_t - C(Ship) + \beta E\left[V(UFO', P')\right]\right\} \tag{2.5}$$

subject to the law of motion (2.2). Let $\mu(UFO, P) = \frac{\partial V(UFO,P)}{\partial UFO}$, the shadow price of an unfilled order and π_t the Karush-Kuhn-Tucker multiplier on constraint (2.4). The first order necessary conditions are

$$\mu_t = P_t - C'(Ship_t) \tag{2.6}$$

$$\pi_t = \mu_t - \beta E[\mu_{t+1}] \tag{2.7}$$

$$\pi_t(UFO_t - Ship_t) = 0 \tag{2.8}$$

Proposition 1. *The shadow price of unfilled orders μ_t is decreasing when the unfilled orders to shipments ratio is increasing.*

Proof: See Appendix B.

Corollary 1. *Away from the constraint $Ship(UFO, P)$ approaches a concave function $S(P)$, such that $C''(S(P))S'(P) = 1$*

Proposition (1) ties the cyclicality of the unfilled orders to shipments ratio to that of the shadow price μ, which from equation (2.6), is equal to the price markup. If $C'(Ship(UFO, P))$ is convex in prices, then μ decreases with P and the unfilled orders to shipments ratio is procyclical. If $C'(Ship(UFO, P))$ is concave in prices, the opposite will be true. To discuss the shape of the policy function $Ship(UFO, P)$ I have yet to establish properties for $NO(P)$.

Figure (2.6) shows, for given UFO, the value of the constraint UFO^b (dashed line), the policy function for shipments $Ship(UFO, P)$ (solid line) and the level of new orders $NO(P)$ (dotted line) for the cases when $\frac{\partial^2 NO(P)}{\partial P^2} > 0$ (panel a) and $\frac{\partial^2 NO(P)}{\partial P^2} < 0$ (panel b). From equation (2.2) we have that end-of-period unfilled orders accumulate, $\Delta UFO > 0$, whenever $NO > Ship$. In panel (a), with convex $NO(P)$, this happens when new orders are high, as is the case in the data (see Figure (2.4)). The opposite is true when $NO(P)$ is a concave as shown on panel (b).

$Ship(UFO, P)$ approaches the concavity (convexity) of new orders as it approaches the constraint. Making $Ship(UFO, P)$ less concave (convex) than new orders. This creates the pattern of accumulation of unfilled orders that we see in Figure (2.6). This rules-out concave functional forms for new orders as they generate countercyclical accumulation of unfilled orders.

Proposition 2. *If $NO(P)$ is convex then marginal cost $C'(Ship(P))$ is convex*

Proof. Follows from Corollary 1. See Appendix B □

From Proposition 2 it follows that $\mu(P, UFO)$ is countercyclical which implies from Proposition 1 that the unfilled orders to shipments ratio is procyclical.

Table (2.4) shows simulated moments from a calibration of the model under the assumption of quadratic cost of shipments and quadratic new orders in prices. I refer to this as the Baseline (partial equilibrium) specification. Targeted moments are marked with boxes. The functional forms are

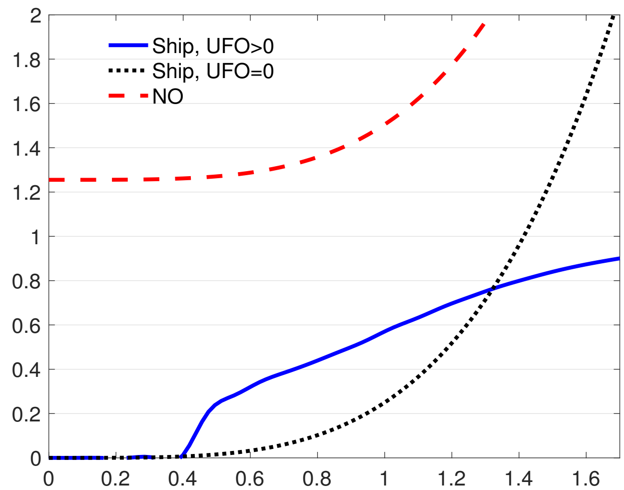
$$C(Ship) = \frac{b}{2}Ship^2 \;\; , \;\; NO(P) = \frac{a}{2}P^2$$

$$ln(P_t) = \rho ln(P_{t-1}) + \varepsilon_t$$

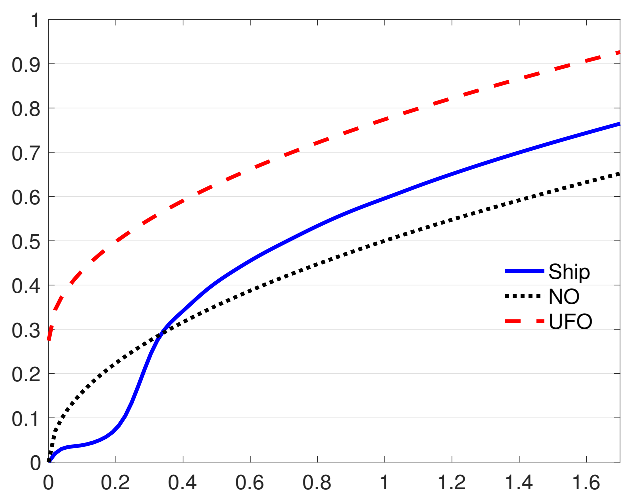
With ε_t i.i.d. innovations from a Normal distribution with mean zero and standard

Figure 2.6: Shipments, policy function

(a) Convex new orders



(b) Concave new orders



Notes: Generated using the policy function from a global solution method assuming quadratic cost of shipments. Panel(a) New orders are assumed to be quadratic in prices. Panel(b) New orders are proportional to the square root of prices deviation calibrated to match the standard deviation of new orders[16]. The persistence of prices, ρ is calibrated to match the persistence on new orders. Parameters a and b target $Corr(\Delta UFO_t, NO_t) = 0.73$ and $\sigma_{Ship}/\sigma_{NO}$, respectively. The model does a relatively good job at matching untargeted moments, generating persistent unfilled orders, shipments and delivery lags. The two prominent exceptions are the cyclicality and volatility of the delivery lag. As expected from the theoretical analysis, the model produces a procyclical delivery lag. Further, it is three times as volatile as new orders.[17].

The results of this section point towards an additional mechanism, different from cost smoothing, to rationalize the cyclicality of the unfilled orders to shipments ratio. A key factor is the cyclcicality of the shadow price of unfilled orders. In the current setup, the shadow price of an unfilled order is the price markup, as the firm gives up a shipment to accumulate unfilled orders. This generates a countercyclical shadow price of unfilled orders as markups in this setup are countercyclical. It is relatively more costly for the producer to accumulate unfilled orders during downturns, when markups are high, leading to the countercyclical ratio. A mechanism that increases the value of an unfilled order during downturns is a candidate to explain the cyclicality of the ratio. In the following section, I make an argument for a financing friction that gives value to unfilled orders as collateral.

---

[16]Moments from NO, UFO and $Ship$ are computed from HP-filtered log-variables. Moments for the ratio of unfilled orders to shipments are computed from the HP-filtered ratio in levels

[17]This implies a ratio of unfilled orders to shipments fifteen times as volatile as GDP

Table 2.4: Moments from the data and the partial equilibrium model

	New orders NO	
	Data	Model
$Corr(NO_t, NO_{t-1})$	0.85	$\boxed{0.88}$
σ_{NO}	0.08	$\boxed{0.08}$
	End-of-Period UFO^{end}	
	Data	Model
$Corr(NO, UFO^{end})$	0.36	0.48
$Corr(UFO_t^{end}, UFO_{t-1}^{end})$	0.94	0.99
$\sigma_{UFO^{end}}/\sigma_{NO}$	0.88	0.52
	Shipments $Ship$	
	Data	Model
$Corr(NO, Ship)$	0.66	0.96
$Corr(Ship_t, Ship_{t-1})$	0.91	0.90
$\sigma_{Ship}/\sigma_{NO}$	0.65	$\boxed{0.68}$
	Delivery lag $dlag$	
	Data	Model
$Corr(NO, Rat)$	-0.26	0.27
$Corr(Rat_t, Rat_{t-1})$	0.91	0.98
σ_{Rat}/σ_{NO}	0.73	3.28

Notes: Moments generated from HP-filtered data from the M3 survey. Model moments correspond to HP-filtered data simulated for one thousand periods after discarding a 150 periods burn-in. Simulations use a policy function obtained from a global solution method

2.4 A model of capital goods producers with financing constraints

Assume that the capital goods producer from the previous section faces a working capital constraint[18]. Every period the producer must borrow funds in order to pay a fraction κ of the cost of production up-front. The loan is paid back, together with a borrowing cost at the end of the period. I assume that the producer can pledge unfilled orders as some form of collateral, making the borrowing cost a decreasing function, $R(UFO)$ of unfilled orders.[19] The first order conditions are

$$\mu_t = P_t - C'(Ship_t) + \kappa(-R'(UFO_t)C(Ship_t) - C'(Ship_t)R(UFO_t)) \tag{2.9}$$

$$\mu_t = \pi_t + \beta E[\mu_{t+1}] - \kappa C(Ship_t)R'(UFO_t) \tag{2.10}$$

Away from the constraint μ_t approaches $-\kappa R'(UFO_t)C(Ship_t) \geq 0$. I further assume that $R''(UFO) > 0$ so that μ_t is decreasing in UFO_t and increasing in $Ship_t$, making μ decreasing as the unfilled orders to shipments ratio increases. Through the financing friction, $R(UFO)$ gives unfilled orders an additional value. When shipments are low, increasing unfilled orders is costly because of the high markup. However, decreasing unfilled orders is also costly, as it increases the shadow price through $-R'(UFO_t)C(Ship_t)$. The producer faces an additional tradeoff when reducing unfilled orders, it gains the price markup but increases its borrowing costs.

[18] My setup for a working capital constraint is based on the work of *Neumeyer and Perri* (2005) and *Jermann and Quadrini* (2012)

[19] In this section I make make R a function of only UFO for exposition purposes. I explore a different specification including the amount borrowed in quantitative model in Section 2.6.

Figure (2.7) shows the policy functions for $Ship(UFO, P)$ and $\mu(UFO, P)$ under the Baseline calibration for different values of κ. I assume a functional form for the borrowing cost given by $R(UFO) = \xi UFO^{\varsigma}$. I calibrate the value of $zeta$ to -0.06 given estimates from the firm-level dataset. I discuss this estimation in in Section (2.4). The value of ξ is calibrated so that, on average, the cost of borrowing is 4% at an annual rate, the average financing cost in my dataset. In panel (a), as the firm has to borrow a larger share of the production costs, the policy function for shipments flattens. The producer reduces its unfilled orders by less when prices are low and increases them by more when prices are high. On panel (b), the shadow price of unfilled orders $\mu(UFO, P)$ turns from decreasing in prices to increasing as κ increases. As argued, a procyclical shadow price implies a countercyclical unfilled orders to shipments ratio.

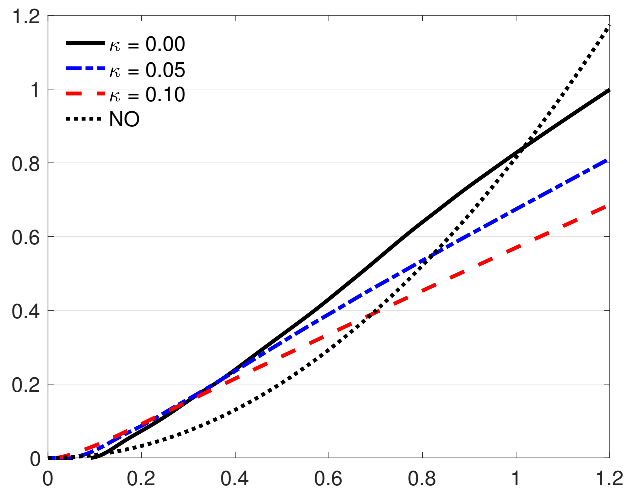
Table (2.5) shows the estimated moments a calibration of the model with financial friction. I call this Friction specification. I target the cyclicality of the unfilled orders to shipments ratio to calibrate κ. The calibrated model produces shipments with a standard deviation 0.80 times that of new orders[20]. This implies shipments are four times as volatile as GDP which is still within the range considered for investment. The model does a little worst than the baseline in generating volatile unfilled orders. Finally, the Friction model does a much better job matching the volatility of the unfilled orders to shipments ratio at 0.62 times that of new orders or about three times the volatility of GDP.

In general, the model does a good job of matching targeted and untargeted moments. It manages to produce a countercyclical unfilled orders to shipments ratio with the volatility that we see in the data. This shows that the financing friction mechanism can rationalize the behavior of the ratio within an otherwise standard

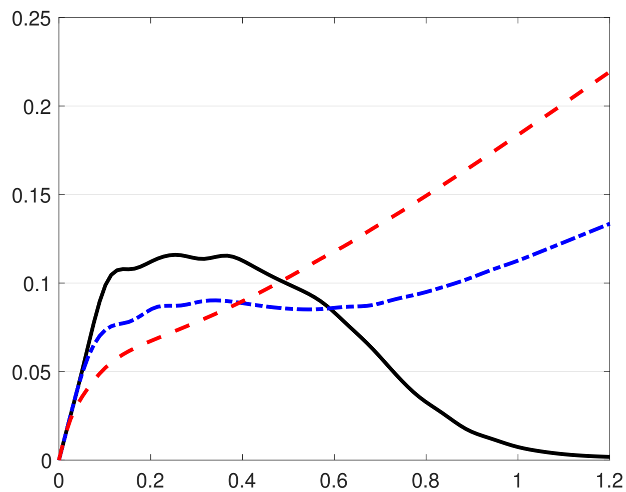
[20]Given the simplicity of the model, there is a tradeoff in the calibration exercise. Increasing the value of κ makes the ratio more countercyclical but it also increases the volatility of shipments.

Figure 2.7: Policy functions, given UFO, for different values of κ

(a) $Ship(UFO, P)$



(b) $\mu(UFO, P)$



Notes:Generated using the policy function from a global solution method assuming quadratic cost of shipments.

Table 2.5: Moments from the data and the model with a financing constraint

	Data	Baseline	Friction
	New orders *NO*		
	Data	Baseline	Friction
$Corr(NO_t, NO_{t-1})$	0.85	0.88	0.87
σ_{NO}	0.08	0.08	0.08
	End-of-Period UFO^{end}		
	Data	Baseline	Friction
$Corr(NO, UFO^{end})$	0.36	0.48	0.77
$Corr(UFO^{end}_t, UFO^{end}_{t-1})$	0.94	0.99	0.98
$\sigma_{UFO^{end}}/\sigma_{NO}$	0.88	0.52	0.29
	Shipments *Ship*		
	Data	Baseline	Friction
$Corr(NO, Ship)$	0.66	0.96	0.98
$Corr(Ship_t, Ship_{t-1})$	0.91	0.90	0.91
$\sigma_{Ship}/\sigma_{NO}$	0.65	0.68	$\boxed{0.80}$
	Delivery lag *dlag*		
	Data	Baseline	Friction
$Corr(NO, dlag)$	-0.26	0.27	$\boxed{-0.26}$
$Corr(dlag_t, dlag_{t-1})$	0.91	0.98	0.79
$\sigma_{dlag}/\sigma_{NO}$	0.73	3.28	0.62

Notes: Moments generated from HP-filtered data from the M3 survey. Model moments correspond to HP-filtered data simulated for one thousand periods after discarding a 150 periods burn-in. Simulations use a policy function obtained from a global solution method cost-smoothing framework. In the following section I provide empirical results to build a story on how financing constraints affect the production of capital goods.

2.5 The role of financing constraints in capital goods production

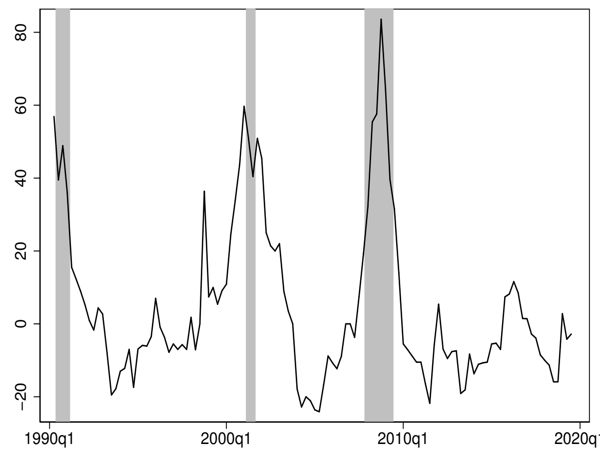
In this section I provide evidence in favor of the financing constraint mechanism. There are three parts to this section, first, evidence of credit conditions tightening during downfalls. Second, evidence of heterogeneous responses of capital producers according to their financing conditions. Third, evidence on the effect of unfilled orders on the borrowing costs.

Cyclicality of credit conditions

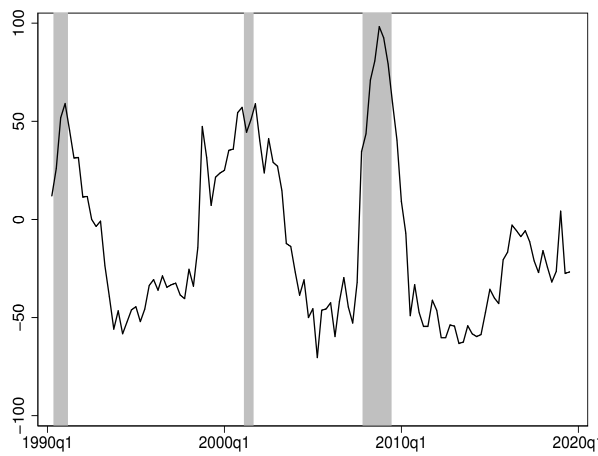
Figure (2.8) presents data from the Senior Loan Officers Opinion Survey conducted by the Board of Governors of the Federal Reserve System. The responses in both panels correspond to conditions for commercial and industrial loans to medium and large firms. Panel (a) shows through time, the percentage of respondents that reported tightening credit standards minus the percentage that reported loosening them. When this number is positive, more respondents are tightening credit conditions. When negative more respondents are loosening them. For example, the mid 2000's correspond to a period of loose credit conditions leading up to the financial crisis, when credit conditions severely tightened. Panel (b) shows the percentage of respondents that reported increasing credit spreads minus the percentage of those who reported decreasing spreads. For both questions there is a clear cyclical pattern with peaks in recessions, making credit conditions tighter during downturns.

Figure 2.8: Conditions on commercial and industrial credit to medium and large firms

(a) Tighter conditions



(b) Higher spreads



Notes: Data from the Senior Loan Officer Opinion Survey of the Board of Governors of the Federal Reserve System. Data corresponds to responses about commercial and industrial loans for medium and large firms. Panel (a): percentage of respondents that report tightening credit standards minus percentage that reported loosening them. Panel (b): percentage of respondents that reported increasing credit spreads minus percentage that reported lowering them

2.5.1 Firm-level responses

I use balance sheet data from Compustat to construct two firm-level variables to work as proxy for financial hardship[21]. The leverage-ratio defined as total debt to assets and, financing costs constructed as the ratio of expenses related to credit to total debt. Table (2.6) shows some summary statistics of these variables. The average leverage-ratio in the dataset is 23% with a standard deviation of 20%. The average financing cost, reported at annual rates, is 4.4%[22]. The financing cost one standard deviation above from the mean is roughly 8%. At the 95th percentile the value is almost 14%.[23].

Table 2.6: Summary statistics of financial variables

	Mean	Median	SD	p95
Leverage	0.226	0.199	0.191	0.652
Financing cost	0.044	0.039	0.036	0.138

Notes: Values computed with firm-level data from Compustat for manufacturing firms classified as capital goods producers according to BEA definitions of investment by type, see Appendix A. The period used is 1974 to 2018. All variables are in real terms.

I use lagged values of these variables to measure financial hardship and divide firms into quartiles according to them. Let $Q_{it}^{q,Fin} = 1$ if firm i belongs to the qth quartile in period t according to measure Fin. My empirical specification is given by

$$y_{it} = \delta_i + \delta_t + \beta_4^{\zeta}\zeta_t^m + \sum_{q=1}^{3} \beta_q^{\zeta} Q_{it}^{q,Fin} \zeta_t^m + \gamma_4^{Fin} Fin_{it-1} + Controls_{it} + \varepsilon_{it} \tag{2.11}$$

[21] Appendix A has a description of the dataset and further details on the construction of variables

[22] consistent with the calibration I used in the model of Section 2.4

[23] The calibration of the discount factor $\beta = 0.99$ implies a steady state risk free annual rate of 4%.

where $y_{it} \in \{ln(Ship_{it}), ln(UFO_{it})\}$ and $Fin_{it} \in \{Lev_{it-1}, r_{it-1}\}$. More precisely, I use demeaned versions of the financial variables $(Fin_{it-1} - E[Fin_{is}])$, to ensure that the responses are identified through within-firm variation, following *Ottonello and Winberry* (2019). The covariate ζ_m is a proxy for an exogenous shock to new orders at the type of capital m level.

The heterogeneity of the response across quartiles is captured by the coefficients β_q. When $\beta_q \neq 0$ the response of firms within quartile q differs from the response of firms in the top quartile, the most financially constrained, which serves as control. A value of $\beta_q > 0$ implies a stronger response for firms in quartile q compared to the control. The total response of a firm in quartile q is given by $\beta_q + \beta_4$.

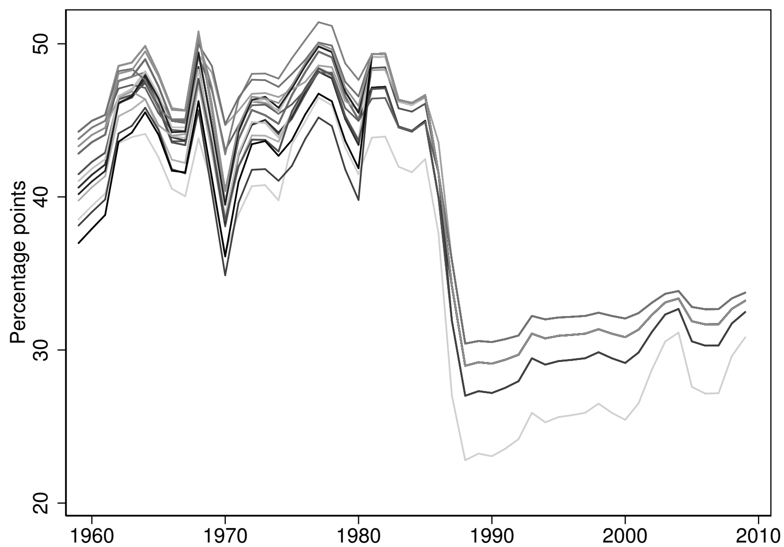
For the value of ζ I use the comprehensive tax subsidy described in *House and Shapiro* (2008) and *House et al.* (2017). The formula to construct ζ is

$$\zeta_t^m = ITC_t^m + \tau_t^\pi Z_t^m$$

where ITC_t^m is the value of the Investment Tax Credit for capital of type m. Z_t^m are depreciation allowances for capital of type m and τ^π is the corporate tax rate. The comprehensive tax subsidy works as a proxy for unfilled orders, *House et al.* (2017) find semi-elasticities of capital goods purchases with respect to the comprehensive tax subsidy of about 2% using the period between 1974 and 2009. I restrict the sample for my estimation to 1978-1990 for a few of reasons. First, this period includes the full and permanent repeal of the ITC, providing strong variation in $zeta$. Second, the different legislation acts that change the levels of the ITC (and ζ) in the period, are classified as tax changes for exogenous reasons to the cycle in *Romer and Romer* (2010). Third, *House et al.* (2017) find that for the response of 2% on investment estimated in the full period half corresponds to purchases of imported goods. Additionally, they find that the share of imports of capital goods has steadily risen through time, allowing to conjecture a weaker response of U.S. capital producers to changes in tax incentives in later periods, for example, the rounds of Bonus Depreciation[24].

Figure (2.9) shows the levels of the comprehensive tax subsidy by type of capital [25]. There is variation across different types of capital, with differences as large as about five percentage points, and substantial variation through time. Particularly, the drop from the repeal of the ITC is the dominant change in the series.

Figure 2.9: Comprehensive tax subsidy



Notes: Data on the comprehensive tax subsidy from House et al. (2017) provided by Christopher House. The period considered corresponds to part of the lifespan of the Investment Tax Credit

The first two columns of Table (2.7) shows the results of estimating equation (2.11) on the firm level data using the leverage-ratio to sort the firms into quartiles. Firms at the top quartile, the control, are the most financially constrained. The semi-elasticity of shipments to the tax incentive is 3.3% for this group. The estimate

[24]Using the entire period with a specification without the financial constraint variables, I find responses to the tax incentives that are not significantly different from zero. As my goal is to study the heterogeneous response rather than the effect of the stimulus, I choose the period for which there is a stronger response

[25]The classification by type of capital and matching between Compustat and the comprehensive tax subsidy data is discussed in Appendix A

is higher than the result on purchases of capital goods found in *House et al.* (2017).

Moving to the top middle quartile, the response is not significantly different from that of the control group. The bottom middle quartile however, is significantly larger both in statistical and economical sense. A 1% increase in the tax incentive causes a 3.9% increase in shipments for unconstrained firms. Firms in all other quartiles respond more modestly with a 3.3% increase in shipments. Similarly, a 1% increase in the tax incentive, increases unfilled orders for constrained firms by 3.2% while for the unconstrained firms in the bottom middle quartile, unfilled orders only increases 2.6%. The semi-elasticity of the unfilled orders to shipments ratio is given by

$$\frac{\partial log(UFO_t/Ship_t)}{\partial \zeta} = \frac{\partial log(UFO_t)}{\partial \zeta} - \frac{\partial log(Ship_t)}{\partial \zeta}$$

The elasticity of the ratio is -0.13% for the constrained firms but -1.36 for producers in the bottom middle quartile. Conditional on a positive new order, unconstrained firms will lower their delivery lag by much more. This provides evidence of the role of the financing constraint mechanism in the cyclical behavior of shipments and unfilled orders. In downturns, when firms are financially constrained they respond to a new order by accumulating more unfilled orders relative to shipments than they would during an expansion, when credit conditions are more slack, leading to an increasing ratio of unfilled orders to shipments.

As a check, the last two columns of Table (2.7) show the results of estimating equation (2.11) using financing costs to sort firms into quartiles. As before, the top quartile is the most constrained and my control group. The magnitude of the responses is similar to the previous results. A 1% increase in tax incentives leads to a 3.75% increase of shipments for the more constrained firms. In the middle quartiles, where firms are unconstrained, the shipments response is significantly higher in statistical and economical sense. These unconstrained firms increase their shipments by 4.14% consistent with my previous results.

Table 2.7: Estimated responses to a 1% change in tax incentives

	Quartiles by leverage-ratio		Quartiles by financing cost	
	$ln(Ship)$	$ln(UFO)$	$ln(Ship)$	$ln(UFO)$
$Q1$	3.547	2.867	3.621	3.516
$diff - Q4$	0.206	-0.340	-0.126	-0.190
	(0.213)	(0.145)	(0.219)	(0.102)
$Q2$	3.957	2.607	4.147	3.597
$diff - Q4$	0.616	-0.600	0.400	-0.109
	(0.218)	(0.392)	(0.209)	(0.087)
$Q3$	3.277	3.045	4.138	3.660
$diff - Q4$	-0.064	-0.162	0.391	-0.046
	(0.190)	(0.346)	(0.163)	(0.063)
$Q4$	3.341	3.207	3.747	3.706
	(1.603)	(1.759)	(1.647)	(1.751)
N	4283	4283	4283	4283

Notes:

$$y_{it} = \delta_i + \delta_t + \beta_4^{\zeta}\zeta_t^m + \sum_{q=1}^{3} \beta_q^{\zeta} Q_{it}^{q,Fin} \zeta_t^m + \gamma_4^{Fin} Fin_{it-1} + Controls_{it} + \varepsilon_{it}$$

Estimated using firm-level data from Compustat matched with data on the Comprehensive tax subsidy from House et al. (2017). Fin represents either the demeaned leverage-ratio or demeaned financing cost, both variables winsorized at the first and 99th percentiles. Standard errors are clustered[26] at the firm and type of capital-year level[27] . Appendix A provides details on the merging process. Controls include value of assets (in logs), firm age, employment level (in logs) and Lerner index

Unfilled orders and borrowing cost

The borrowing cost I have proposed is a decreasing function of unfilled orders. My argument here is that unfilled orders hold value as an asset either because they are backed by accounts receivable or because the firm accumulates work-in-process with each new order. The latter is a feature that I include in the general equilibrium model of Section 2.6. I estimate the elasticities of the financing cost with respect to unfilled orders and total debt, according to the following specification.

$$ln(r_{it}) = \delta_i + \delta_t + \zeta_1 ln(UFO_{it}^{end}) + \zeta_2 ln(Debt_{it}^{end}) + Controls_{it} + \varepsilon_{it} \tag{2.12}$$

Table (2.8) shows the estimated coefficients from equation (2.12). Both elasticities are statistically significant. The elasticity with respect to unfilled orders, although small, may be economically significant. Given an average financing cost of 4% at an annual rate the decrease in financing costs following a 1% increase in unfilled orders drops the financing costs by a quarter of a percentage point at an annual rate.

Table 2.8: Elasticities of financing costs to unfilled orders and total debt

	(1) l_fincost
$log(UFO)$	-0.06
	(0.009)
$log(Debt)$	0.31
	(0.003)
N	15804

Notes:

$$ln(r_{it}) = \delta_i + \delta_t + \zeta_1 ln(UFO_{it}^{end}) + \zeta_2 ln(Debt_{it}^{end}) + Controls_{it} + \varepsilon_{it}$$

Estimated using firm-level data from Compustat as described in Appendix A. The financing cost corresponds to the demeaned variable winsorized at the first and 99th percentile. Errors are clustered at the firm and year level. Controls include value of assets (in logs), firm age, employment level (in logs) and Lerner index

2.6 A business cycle model with capital goods producers

In this section I embed the problem of the capital goods producer with a financial constraint into an otherwise standard business cycle model. First I will describe some details about the pricing of new orders and shipments, then the capital goods producer's problem and finally the rest of the economy.

The aggregate stock of beginning-of-period unfilled orders evolves according to

$$UFO_t^b = UFO_{t-1}^b - Ship_{t-1} + NO_t \tag{2.13}$$

Shipments at time t are priced at the average price of the stock of unfilled orders, $\bar{P}_t$. The assumption here is that each firm ships an equal proportion of the unfilled orders it has. At the moment of placing a new order the household pays a share κ_1 of its value at market price P_t and will pay the remaining share $(1-\kappa_1)$ at this average price upon receiving the shipments[28]. The price value of the stock of unfilled orders evolves according to

$$\bar{P}_t UFO_t^b = \bar{P}_{t-1}(UFO_{t-1}^b - Ship_{t-1}) + P_t NO_t \tag{2.14}$$

Equation 2.14 can be written as

$$\bar{P}_{t+1} = \left(1 - \frac{dUFO_t^b}{UFO_{t+1}^b}\right)\bar{P}_t + (P_t - \bar{P}_t)\frac{NO_t}{UFO_{t+1}^b} \tag{2.15}$$

[28] I make this assumption given the saliency of price-scalation clauses in contracts. However, I reproduce the results from the model without this assumption in Appendix D. I find that none of the results in the model analysis are driven solely or mainly by this assumption.

Capital producer

There is a unit measure of identical capital goods producers. The representative capital goods producer takes the market price of capital goods P_t as given, has agency on the level of new orders no_t^{kp} it accepts and decides on a production schedule to maximize profits. The timing at which different events happen within the period is important to describe the producer's problem. Each period t is divided into beginning of period $t-$ and end of period $t+$.

Beginning of period (first stage) $t-$

In this stage, the producer receives new orders no_t^{kp} and payment for a fraction κ_1 of their market value. All orders taken in are projects which must be started at a cost $\Phi(no_t^{kp})$ in units of the final good. These projects increase the stock of beginning-of-period unfilled orders ufo_t^{kp} which evolves according to

$$ufo_t^{kp} = ufo_{t-1}^{kp} - Ship_{t-1} + no_t^{kp} \tag{2.16}$$

The producer purchases consumption goods I_t to be used as inputs to move started projects into a production line, according to a decreasing returns technology $x_t = f(I_t)$. The x_t projects increase the stock of work-in-process X_t under the constraint

$$X_t \leq ufo_t^{kp} \tag{2.17}$$

I will discuss how X_t turns into shipments and the evolution of X_t in the second stage of the period. The producer must pay the totality of the cost of new orders $\Phi(no_t^{kp})$ as well as a fraction $\kappa_2 I_t$ of the production inputs using working capital given by

$$
\begin{aligned}
WC_t = \kappa_1 P_t no_t^{kp} - \Phi(no_t^{kp}) + D_t \\
D_t \geq 0 \quad WC_t \geq \kappa_2 I_t
\end{aligned}
\tag{2.18}
$$

The term D_t corresponds to an intratemporal loan from financial intermediaries which procure their funds from the households. The loan is paid back in the second stage of the period at a cost schedule given by

$$
R_t = R(ufo_t^{kp}, D_t) = \xi(ufo_t^{kp})^{\zeta_1} D_t^{\zeta_2}, \quad R_t \geq 0 \tag{2.19}
$$

Financing costs depend positively on the amount borrowed D_t and negatively on the unfilled orders ufo_t^{kp} that can be pledged as collateral. Unfilled orders, either started projects or work-in-process, are essential for production which gives them value as assets. The rate R_t reflects a risk of default which I do not model explicitly but for which I make the following two assumptions

1. The risk of default does not affect the shipments made in the period and a producer that defaults continues operations as one more of the identical producers.

2. The expected and realized return to the households is zero. The households lend out D_t in the first stage of the period and get D_t back in the second stage, before consumption takes place.

Table (2.9) summarizes the transactions made in stage 1.

End of period (second stage) $t+$

In the second stage a fraction θ of the work-in-process turns into shipments. The stock of work-in-process X_t evolves according to

$$
X_t = (1-\theta)X_{t-1} + x_t \tag{2.20}
$$

Table 2.9: Producers accounting: stage 1

Working capital	
$\kappa_1 P_t no_t^{kp}$	$\kappa_2 I_t$
D_t	$\Phi(no_t^{kp})$

Accounts payable	
	$(1+R_t)D_t$
	$(1-\kappa_2)I_t$

Revenue	
	$\kappa_1 P_t no_t^{kp}$

Operation costs	
$R_t D_t$	
I_t	
$\Phi(no_t^{kp})$	

Notes: T-ledger of transactions made by the capital goods producer during the first stage. Following standard practices, left column corresponds to debits, right to credits. Revenue accounts are credit accounts, costs accounts are debit accounts.

The producer sends shipments and receives a fraction $1-\kappa_1$ of their value at the average price of unfilled orders $\bar{P}_t$. Finally, the firm pays back the amount borrowed D_t with the cost of borrowing $R_t D_t$[29], pays the remaining fraction $(1-\kappa_2)I_t$ of consumption goods and makes dividend payments for the amount of the profit to the household. Table (2.10) shows the transactions in this stage marked with boxes.

The producers problem is to maximize profits according to

$$\max \sum_{t=0}^{\infty} E\left[\beta^t u'(C_t)(\kappa_1 P_t no_t^{kp} + (1-\kappa_1)\bar{P}_t \theta X_t - I_t - \Phi(no_t^{kp}) - D_t R(ufo_t^{kp}, D_t))\right] \tag{2.21}$$

subject to the laws of motion (2.16), (2.20), the constraint on work-in-process (2.17) and the working capital constraint (2.18).

[29] Loan and borrowing cost are paid to the financial intermediary which in turn gives the returns to the household. As assumed, the default rate is such that the return to the household is zero. The role of the financial intermediary is that all households loan to all producers in equal proportions. This guarantees that the expected return of zero equals the actual return

Table 2.10: Producers accounting: stage 2

Working capital

$\kappa_1 P_t no_t^{kp}$	$\kappa_2 I_t$
D_t	$\Phi(no_t^{kp})$
$\boxed{\kappa_2 I_t}$	$\boxed{\kappa_1 P_t NO_t}$
$\boxed{\Phi(no_t^{kp})}$	$\boxed{D_t}$

Accounts payable

$\boxed{(1+R_t)D_t}$	$(1+R_t)D_t$
$\boxed{(1-\kappa_2)I_t}$	$(1-\kappa_2)I_t$

Revenue

	$\kappa_1 P_t NO_t$
	$\boxed{(1-\kappa_2 \bar{P}_t \theta X_t}$

Operation costs

$R_t D_t$	
I_t	
$\Phi(no_t^{kp})$	

Dividend payments

$\boxed{\kappa_1 P_t no_t^{kp}}$	$\boxed{I_t}$
$\boxed{(1-\kappa_1)\bar{P}_t \theta X_t}$	$\boxed{R_t D_t}$
	$\boxed{\Phi(no_t^{kp})}$

Notes: T-ledger of transactions made by the capital goods producer during the second stage. Following standard practices, left column corresponds to debits, right to credits. Revenue accounts are credit accounts, costs accounts are debit accounts.

Household

There is a measure one of identical households that own capital K_t which they use together with their labor to produce the consumption good through a technology

$$F(K,N) = \varphi_t K_t^{\alpha} N_t^{1-\alpha} \tag{2.22}$$

where the productivity shifter φ_t follows a first order Markov process. To purchase capital the household makes new orders no_t^{hh} at the beginning of the period and pays a fraction κ_1 of their market price up-front. New orders increase the stock of the household's unfilled orders ufo_t^{hh}. At the end of the period, the household receives shipments of capital goods $\ell_t ufo_t^{hh}$ and pays a fraction $(1-\kappa_1)$ of their value according to the average value of the stock of unfilled orders. The variable ℓ_t summarizes the production schedule chosen by the capital goods producer and taken as given by the household.[30] The capital stock and the stock of unfilled orders evolve according to

$$K_{t+1} = (1-\delta)K_t + \ell_t ufo_t^{hh} \tag{2.23}$$

$$ufo_t^{hh} = (1-d)(1-\ell_{t-1})ufo_{t-1}^{hh} + no_t^{hh} \tag{2.24}$$

The capital producers pay dividends Π_t to the households. The household budget constraint is given by

$$C_t + P_t no_t^{hh} + \bar{P}_t \ell_t ufo_t^{hh} + B_{t+1} = (1+r_{t-1})B_t + F(K_t, N_t) + \Pi_t \tag{2.25}$$

where B_t represents the household position on a one period bond. The household

[30]The rate at which the household's investment turns into productive capital, ℓ_t, fills-in the place of the marginal-efficiency-of-investment (MEI) wedge introduced by *Justiniano et al.* (2011), who find it to be the main driver of U.S. business cycles in the post-war period. This model points towards possible micro-foundations for this type of shocks.

maximizes utility according to

$$\max \sum_{t=0}^{\infty} \beta^t (u(C_t) - \nu(N_t)) \tag{2.26}$$

subject to (2.24), (2.23) and (2.25). The first order necessary conditions are collected on Appendix D.

Aggregation

Let NO_t and UFO_t be the aggregate level of new orders and unfilled orders, respectively. The aggregate resources constraint in this economy is

$$C_t + I_t + \Phi(NO_t) + D_t R(UFO_t, D_t) = F(K_t, N_t) \tag{2.27}$$

Aggregate unfilled orders relate to aggregate beginning of period unfilled orders by

$$UFO_t = UFO_t^b - Ship_t \tag{2.28}$$

Given the assumptions on households and producers the model aggregates trivially. In equilibrium we have that

$$NO_t = no_t^{hh} = no_t^{kp} \quad , \quad UFO_t^b = ufo_t^{hh} = ufo_t^{kp}$$

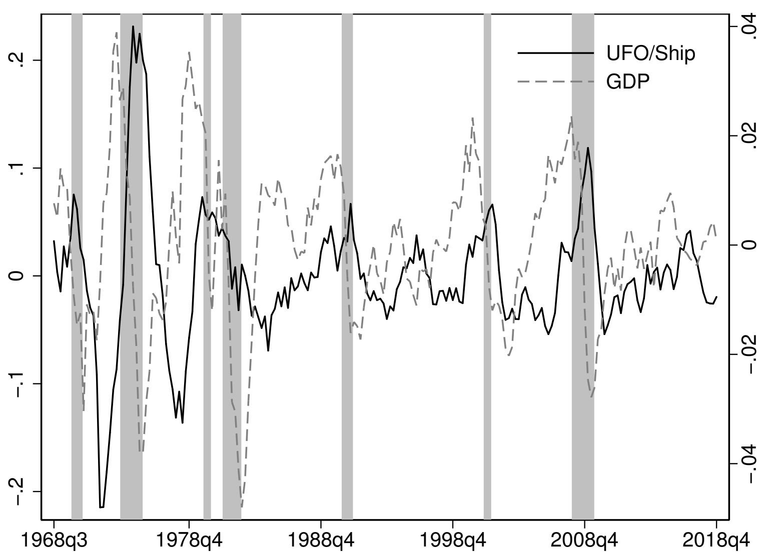
$$Ship_t = \ell_t UFO_t^b = \theta X_t$$

For a full Equilibrium definition see Appendix D

Non-linearities and Solution method

Constraints (2.17) and (2.18) are important to understand the cyclical behavior of the producer as they are occasionally binding. On the one hand, the cyclicality of the ratio of unfilled orders to shipments implies that (2.17) does not bind all the time. On the other hand, taking a look back at Figure (2.5), which I reproduce below, we find some evidence of the constraint binding, midway through expansions, when the ratio of unfilled orders to shipments flattens.

Figure 2.5: HP-detrended UFO/Ship ratio and GDP (repeated from page 18)



Notes: HP-filtered ratio of unfilled orders over shipments for "Non-defense equipment excluding aircraft" from the M3 survey and HP-filtered log-GDP from NIPA tables. Recession bands correspond to the NBER recession classification

As for (2.18), the financing friction mechanism relies on the constraint binding in periods when new orders are low and to slack when new orders are high. The producers Euler equation for unfilled orders is given by

$$\mu_t = \beta E\left[\frac{u'(C_{t+1})}{u'(C_t)}\mu_{t+1}\right] + \pi_{1t} - R_1(ufo_t^{kp}, D_t) \tag{2.29}$$

The last element on the right-hand-side adds to the shadow price of unfilled orders, as unfilled orders bring the borrowing costs down when the firm has to borrow, i.e. when (2.18) binds. To preserve the occasionally binding constraints I compute a piecewise-linear approximation around a steady state using the algorithm of *Guerrieri and Iacoviello* (2017). The piecewise-linear policy functions allow for the dynamics of the model to change as the constraints in the model economy switch between binding and slack. In my model, I consider the following 4 regimes spanned from the constraints

Table 2.11: Regimes in the model with occasionally binding constraints

Regime 1	Regime 2	Regime 3	Regime 4
$UFO = X$	$UFO > X$	$UFO = X$	$UFO > X$
$WC > \kappa_2 I$	$WC > \kappa_2 I$	$WC = \kappa_2 I$	$WC = \kappa_2 I$
$D = 0$	$D = 0$	$D \geq 0$	$D \geq 0$

Notes: Regimes spanned by all possible combinations of constraints (2.17) and (2.18).

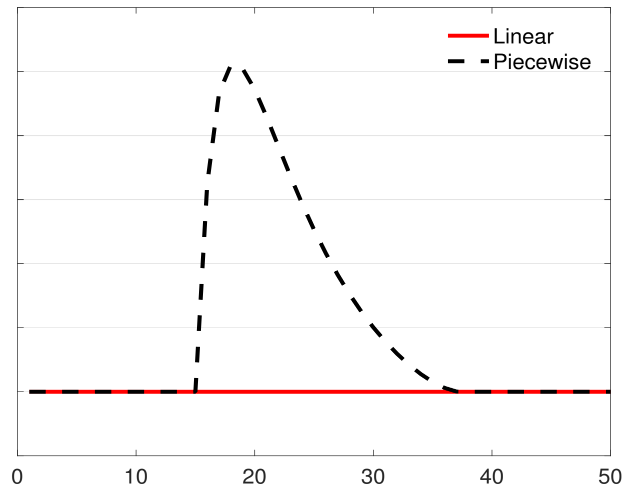
Figure (2.11) shows impulse-response functions of the delivery lag for two cases in which the model economy switches between regimes. In panel (a) the economy starts in a Regime 3 steady state, with $D > 0$ and $UFO = X$. A series of positive innovations to productivity push X away from constraint (2.17) since the firm has a convex cost of producing X. This pushes the unfilled orders to shipments ratio up when the economy switches into Regime 4 with $UFO > X$. In panel (b) the economy starts in a Regime 2 steady state with $D = 0$ and $UFO > X$. A series of negative productivity innovations bring new orders down to the point where (2.18) binds and $D > 0$, switching into Regime 4. This is an example of the mechanism producing a countercyclical unfilled orders to shipments ratio during downturns.

Functional forms and fixed parameters calibration

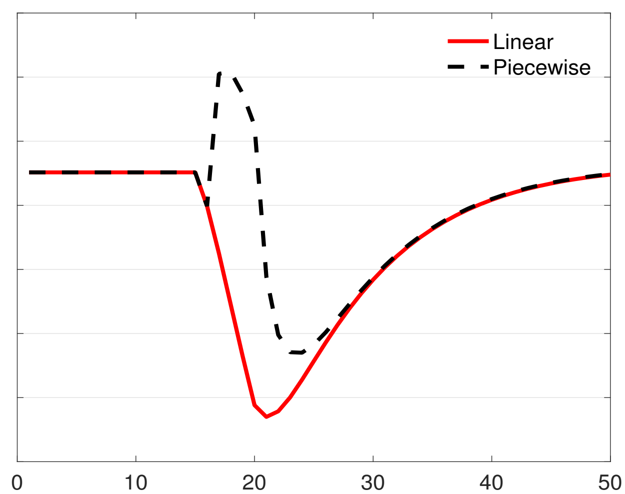
I use the following functional forms and fixed parameters calibration across all quantitative exercises. Following *Christiano et al.* (2005) and *Justiniano et al.* (2011) I

Figure 2.11: Unfilled orders to shipments ratio and occasionally binding constraints

(a) $UFO = X \Rightarrow UFO \geq X$



(b) $WC \geq \kappa_2 I \Rightarrow WC = \kappa_2 I$



Notes: Impulse response function to a series of innovations in productivity. Panel (a) positive innovations. Panel (b) negative innovations. Simulated from piecewise linear policy functions obtained using the algorithm of Guerrieri and Iacoviello (2017) use log-utility for the instantaneous utility function. The disutility of labor function is given by $\nu(N) = \psi\frac{N^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}}$. I calibrate the inverse Frisch elasticity to $\eta = 2$ consistent with the range of values from *Chetty et al.* (2011). I calibrate ψ to match a steady state share of employment of 60%. I use a decreasing returns production function for work-in-process $f(I) = \frac{2I^{\frac{1}{2}}}{b}$ so that the cost of $x = f(I)$ is quadratic in I. Finally, the cost of turning a new order into a started project $\Phi(NO) = \chi NO$ is linear in new orders so that the price P_t remains constant under one of the Baseline specifications. The time unit is one quarter and I calibrate $\beta = 0.99$ accordingly to imply an annual risk free rate in steady state of 4%. Capital depreciation is set to an annual rate of 13.5% in line with the average for the post-war period according to data from the National Income and Product Accounts. I choose $\alpha = 1/3$ for the capital share in the production of the consumption good, which I assume is constant returns to scale. I set the parameters of persistence and variance of the aggregate productivity process as in *King and Rebelo* (1999). All quantitative specifications have steady states under Regime 1 with $UFO = X$, $WC > \kappa_2 I$ and $D_t = 0$. Table (2.12) summarizes the values of the fixed calibration parameters.

Table 2.12: Calibration of fixed parameters

η	Inverse Frisch elasticity	2
β	Discount factor	0.99
δ	Capital depreciation	0.034
α	Capital share of production	1/3
ρ	Persistence of productivity process	0.95
σ_φ	Std dev of innovations to productivity	0.007

Notes: Fixed calibration parameters are common across all specifications and are set according to the standards in the literature

Baseline calibrations

I calibrate the model to produce two baseline specifications. First, a standard investment model, equivalent to an RBC model, with no working capital constraint and no delivery lags. Second, a model with delivery lags similar to that in Section 2.3. I will refer to these two specifications as Standard and Delivery Lag, respectively.

Standard specification Under the calibration for the Standard specification, the model economy will remain under Regime 1 for most productivity innovations. I set $\theta = 1$ so that

$$UFO_t = X_t = \theta X_t = Ship_t = NO_t, \;\; UFO_t = 0, \;\; \frac{UFO_t}{Ship_t} = 0$$

Under the standard specification $P_t = \bar{P}_t = P$, the value of the price in steady state. Since new orders equals shipments under this calibration, I set the parameter χ on the cost of new orders to 1 and calibrate b in the production function of work-in-process to match the ratio of the standard deviations of shipments to GDP. Table (2.13) shows moments of the model alongside their data counterparts. The moments that I target for calibration are Marked with a box. The volatility of shipments is summarized by $\sigma_{Ship}/\sigma_{GDP} = 3.5$ in the data. The model falls short of the target with a maximum attainable value of around 2. This will be true across all calibrations of the model, hence the Standard calibration will serve as my benchmark for shipments volatility to compare against the other specifications. As for the untargeted moments, the model does a good job matching the persistence of shipments but shipments are more procyclical than in the data.

Delivery Lag specification Under the Delivery Lag calibration, I set the parameter κ_1 so that the economy enters Regime 2, with $UFO > X$, with the necessary frequency to target the relative volatility of the unfilled orders to shipments ratio. The parameter θ, which essentially reflects the technical delivery lag given technology, is set to target a steady state unfilled orders to shipments ratio of 1. As before, I set b to target shipments volatility but now I calibrate χ to match the ratio of the standard deviation of new orders to that of shipments, 1.6. Table (2.13) shows on its last column the resulting moments from the model, marked with boxes those targeted in calibration.

As with the Standard calibration, the model falls short of generating enough volatility of shipments to match the data with a value of $\sigma_{Ship}/\sigma_{GDP} = 2$. The other targeted moments fair better. The ratio $\sigma_{NO}/\sigma_{Ship} = 1.3$ is close to the 1.6 target and the volatility of the unfilled orders to shipments ratio matches that of the data. For the untargeted moments, the model does a good job with the volatility of new orders and the persistence of all variables. As with the Standard calibration, all variables are more procyclical in the model than in the data. As expected, the model generates a procyclical unfilled orders to shipments ratio.

In contrast with the Standard calibration, the Delivery Lag one generates variation in unfilled orders and their ratio to shipments by having constraint (2.17) only bind occasionally. Figure (2.12) compares on panel (a) the impulse-response functions of investment between the two calibrations to a positive innovation to productivity that increases GDP by one standard deviation at its peak, around 2%. The peak response of investment is higher at 6.4% under the Standard calibration compared to 4.7% in the Delivery Lag. However, The cumulative response is only slightly higher under the Standard calibration at 1.03 times that of the Delivery Lag one. The response under the Delivery Lag calibration is hump-shaped, consistent with empirical findings and has higher persistence than under the Standard calibration.

Non-linear dynamics The size of the innovations matter because of the nonlinearities in the model. On panel (b) of Figure (2.12) we see the response to an innovation that increases GDP by 5% at its peak. The peak response of investment under the Standard calibration is now twice as big as the peak response under the Delivery Lag calibration. Under the latter, as the marginal cost of producing capital goods increases, constraint (2.17) stops binding and the unfilled orders to shipments ratio increases. This reduces the peak response of investment as unfilled orders accumulate. The cumulative response is only 1.1 times larger under the Standard calibration, as

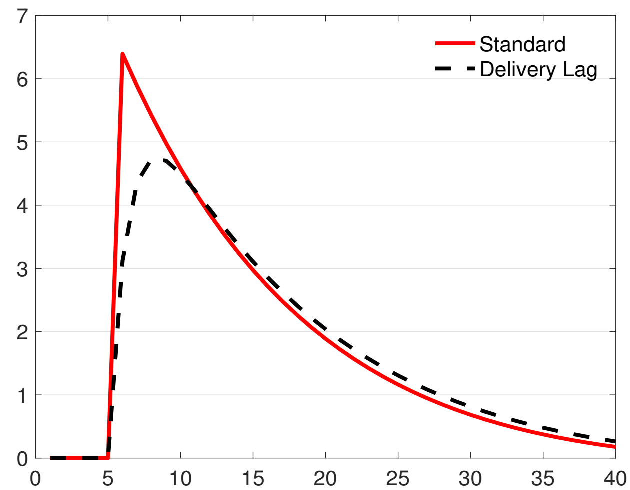
Table 2.13: Moments from the data and the baseline models

	New orders NO		
	Data	Standard	Delivery Lag
$Corr(GDP, NO)$	0.76	0.91	0.91
$Corr(NO_t, NO_{t-1})$	0.80	0.92	0.91
σ_{NO}/σ_{GDP}	5.6	2.0	$\boxed{2.6}$
	End-of-Period UFO^{end}		
	Data	Standard	Delivery Lag
$Corr(GDP, UFO^{end})$	0.36	–	0.82
$Corr(UFO^{end}_t, UFO^{end}_{t-1})$	0.94	–	0.99
$\sigma_{UFO^{end}}/\sigma_{GDP}$	5.0	–	5.2
	Investment $Ship$		
	Data	Standard	Delivery Lag
$Corr(GDP, Ship)$	0.66	0.91	0.94
$Corr(Ship_t, Ship_{t-1})$	0.91	0.92	0.97
$\sigma_{Ship}/\sigma_{GDP}$	3.5	$\boxed{2.0}$	$\boxed{2.1}$
	Delivery lag $dlag$		
	Data	Standard	Delivery Lag
$Corr(GDP, Rat)$	-0.26	–	0.64
$Corr(Rat_t, Rat_{t-1})$	0.91	–	0.99
$\sigma_{Rat}/\sigma_{GDP}$	4.1	–	$\boxed{4.1}$

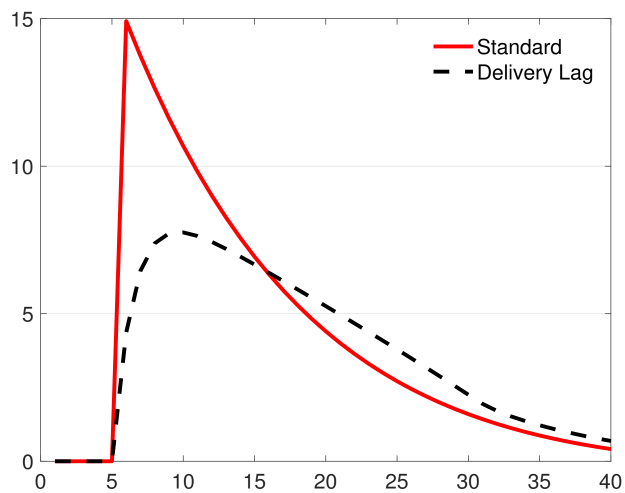
Notes: Moments generated from HP-filtered data from the M3 survey. Model moments correspond to theoretical moments of the linearized model for the Standard calibration and to HP-filtered data simulated for one thousand periods after discarding a 150 periods burn-in for the Delivery Lag calibration. Simulations use a piecewise linear policy function around a steady state obtained with the algorithm of Guerrieri and Iacoviello (2017) the accumulated unfilled orders under the Delivery Lag calibration keep the response of investment up for longer.

Figure 2.12: Response of investment to a positive innovation to productivity

(a) 2% peak response of GDP



(b) 5% peak response of GDP



Notes: Impulse response functions to positive innovations to the productivity process. Responses are generated using the piecewise linear policy function obtained with the algorithm in Guerrieri and Iacoviello (2017), around a non-stochastic steady state. The responses correspond to the real value of shipments, this is, shipments of capital goods times the average price of unfilled orders.

Hump-shaped dynamics The hump-shaped dynamics in the Delivery Lag model are driven by the momentum in the accumulation of work-in-process produced by the technical delivery lag θ. This feature makes each increase in the stock of work-in-process have a (declining) effect on future shipments. For example, If the producer increases the stock of work-in-process after the impulse by x_t, shipments increase by θx_t and the stock of work in process next period X_{t+1} by $(1-\theta)x_t$. Then x_t ha a contribution t shipments next period of $\theta(1-\theta)x_t$ and in general, j periods out, the change made to work in process at time t contributes to shipments at $t+j$ by $\theta(1-\theta)^j x_t$. Figure (2.13) shows on panel (a) the response of investment to the same productivity innovation for different values of *theta*. As θ decreases the peak response falls and the tail of impulse-response function becomes fatter and longer.

Increasing the value of κ_1 makes constraint (2.17) stop binding more frequently[31]. Panel (b) shows the responses holding $\theta = 1$ and increasing the value of κ_1. Increasing κ_1 leads to investment responses that have lower peaks and fatter tails, just as we get from decreasing θ. However, with $\theta = 1$ the response looses its characteristic shape.

Figure 2.14 shows the effect of θ on the responses prices. In panel (a) we can see that θ has little effect on the market price of a new order. In panel (b) we see a hump-shaped response of the average price of an unfilled order with lower peaks and fatter tails as θ decreases. Equation (2.15) shows that the evolution of $\bar{P}_t$ depends on the evolution of X_t, explaining how it inherits the shape of its dynamics.[32]

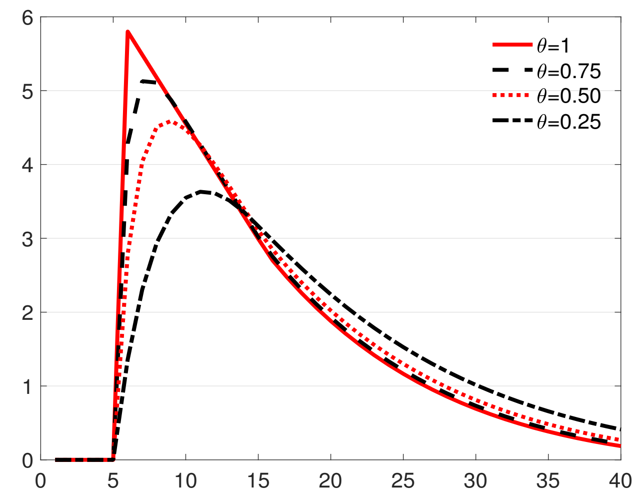
In summary, the Delivery Lag does a relatively good job at matching data moments with the big exception of the negative correlation of the unfilled orders to shipments ratio with GDP. This calibration generates responses of investment that are hump-shaped and non-linear on the size of the shocks. The cumulative responses of investment are similar between the Standard and the Delivery Lag calibration. However, the peak response in the Delivery Lag calibration is lower and its tail is

[31]As κ_1 increases the shadow price π_1, on constraint (2.17) binding, decreases. This brings the steady state of the model closer to where the constraint stops binding.

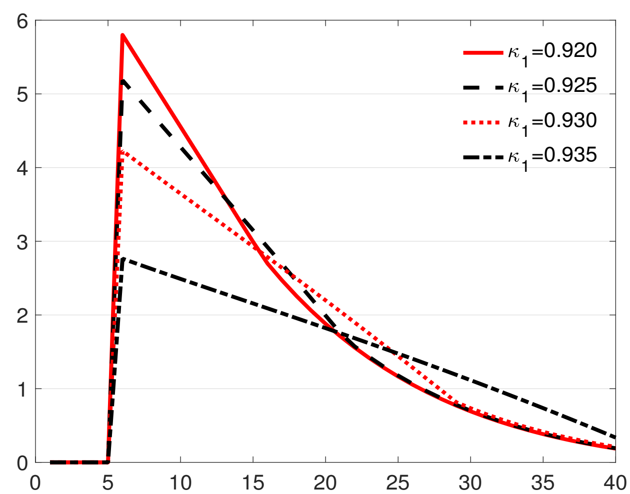
[32]In Appendix D I show the results of the model analysis without the average price assumption by setting $\bar{P}_t = P_t$. None of the conclusions of the analysis rely on this assumption, the hump-shaped response of shipments included.

Figure 2.13: Response of investment to a positive innovation to productivity

(a) Values of steady state delivery lag



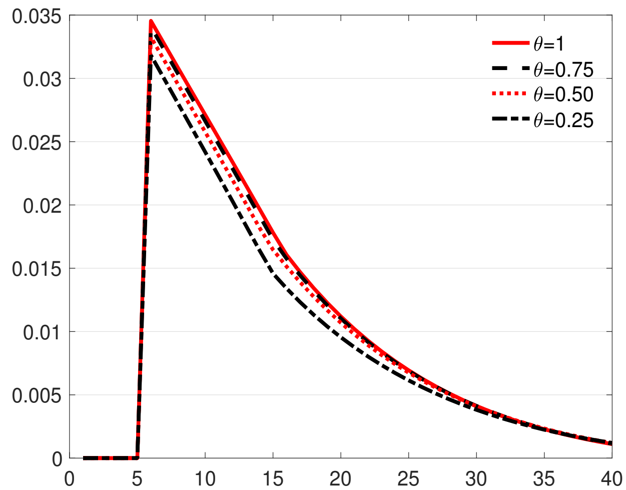
(b) Values of the shadow price of (2.17) binding



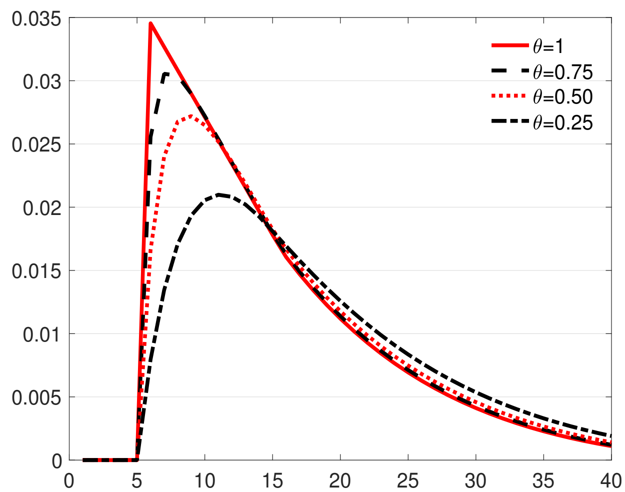
Notes: Impulse response functions to positive innovations to the productivity process. Responses are generated using the piecewise linear policy function obtained with the algorithm in Guerrieri and Iacoviello (2017), around a non-stochastic steady state. The responses correspond to the real value of shipments, this is, shipments of capital goods times the average price of unfilled orders.

Figure 2.14: Responses of the prices of investment to a positive innovation to productivity

(a) Market price of new orders



(b) Average price of unfilled orders



Notes:Impulse response functions to positive innovations to the productivity process. Responses are generated using the piecewise linear policy function obtained with the algorithm in Guerrieri and Iacoviello (2017), around a non-stochastic steady state.

fatter.

Financing friction calibration

Finally, I calibrate the parameters of the borrowing cost function and the share of costs κ_2 that the capital producer must pay up-front. I depart from the procedure followed in Section 2.3 to calibrate some of these parameters. The estimated elasticity of the financing cost to unfilled orders from Section 2.4, $\zeta_1 = -0.06$, is too low for the general equilibrium model to deliver a countercyclical unfilled orders to shipments ratio. I fix the ratio between ζ_1 and the elasticity $\zeta_2 = 0.33$, as estimated in Section 2.4 at 0.19, and calibrate κ_2 and ζ_1 jointly in order to match the correlation between the unfilled orders to shipments ratio and GDP and the ratio of the standard deviations of unfilled orders and GDP. Table (2.14) shows on the right column, the moments generated from this exercise. The calibration fairs slightly better than the baselines at matching the volatility of shipments. For untargeted moments the model does well in matching the persistence of the variables but, once again generates shipments and new orders that are more procyclical than the data. The model does better at matching the low positive correlation between unfilled orders and GDP. Finally, the model achieves the countercyclicality and volatility of the unfilled orders to shipments ratio. In general, I conclude that the model with the financing friction does a good job compared to the baseline specifications and is capable of replicating the cyclical behavior of the unfilled orders to shipments ratio.

2.7 Investment dynamics

In Section 2.6 I discussed two important implications for aggregate investment dynamics, the hump-shaped responses and the non-linear effect of the size of shocks. With the Financial Friction calibration there are two new features to discuss, the model

Table 2.14: Moments from the data and the baseline models

	Data	Standard	Delivery Lag	Fin. Fric.
	New orders NO			
	Data	Standard	Delivery Lag	Fin. Fric.
$Corr(GDP, NO)$	0.76	0.91	0.91	0.92
$Corr(NO_t, NO_{t-1})$	0.80	0.92	0.91	0.92
$\sigma NO/\sigma GDP$	5.6	2.0	$\boxed{2.6}$	$\boxed{2.8}$
	End-of-Period UFO^{end}			
	Data	Standard	Delivery Lag	Fin. Fric.
$Corr(GDP, UFO^{end})$	0.36	–	0.82	0.17
$Corr(UFO_t^{end}, UFO_{t-1}^{end})$	0.94	–	0.99	0.98
$\sigma UFO^{end}/\sigma GDP$	5.0	–	5.2	$\boxed{4.11}$
	Investment $Ship$			
	Data	Standard	Delivery Lag	Fin. Fric.
$Corr(GDP, Ship)$	0.66	0.91	0.94	0.90
$Corr(Ship_t, Ship_{t-1})$	0.91	0.92	0.97	0.97
$\sigma Ship/\sigma GDP$	3.5	$\boxed{2.0}$	$\boxed{2.1}$	$\boxed{2.2}$
	Delivery lag $dlag$			
	Data	Standard	Delivery Lag	Fin. Fric.
$Corr(GDP, dlag)$	-0.26	–	0.64	$\boxed{-0.28}$
$Corr(dlag_t, dlag_{t-1})$	0.91	–	0.99	0.99
$\sigma dlag/\sigma GDP$	4.1	–	4.1	$\boxed{4.3}$

Notes: Moments generated from HP-filtered data from the M3 survey. Model moments correspond to theoretical moments of the linearized model for the Standard calibration and to HP-filtered data simulated for one thousand periods after discarding a 150 periods burn-in for the Delivery Lag and Financial Friction calibrations. Simulations use a piecewise linear policy function around a steady state obtained with the algorithm of Guerrieri and Iacoviello (2017) delivers investment responses that are asymmetric and can have slow recoveries.

Asymmetric responses and State-dependence

The nonlinearities in the model produce an asymmetry between the responses of investment to positive and negative shocks. After a negative shock, the fall in new orders puts downward pressure on working capital. As the financing constraint (2.18) binds and the cost of production increases due to borrowing costs. The capital goods producers accumulate unfilled orders relative to shipments, making the fall in investment stronger. Figure (2.16) compares responses of investment to positive and negative shocks. The positive and negative responses from the Standard and Delivery Lag models are symmetric. The response to a negative shock in the Financial Friction model has a through about half a percentage point farther away from the steady state than the response to a positive shock. Further, the cumulative response to the negative shock is 9.7% larger than the response to the positive shock.

On the other hand, positive shocks put downward pressure on π_1, the shadow price on constraint (2.17). This follows from the producer's Euler equation for unfilled orders, equation (2.29). When the constraint stops binding, the producer accumulates unfilled orders, weakening the response of investment. This is the case on panel (b) of Figure (2.12).

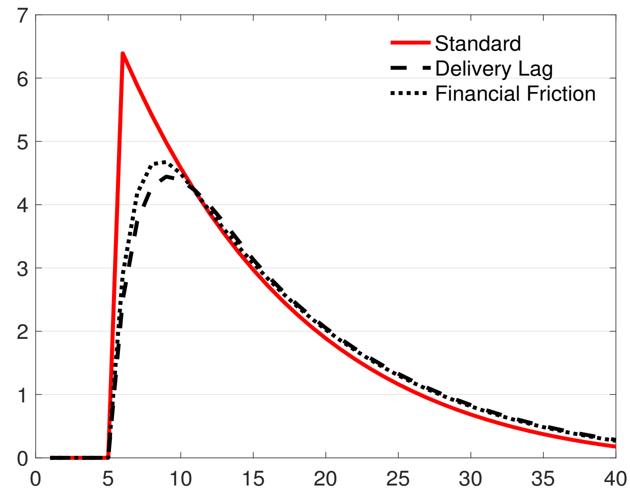
Together, these two mechanisms produce the state-dependence discussed in Section 2.3. A lower elasticity of shipments with respect to GDP in expansions than in downturns. Meanwhile, the elasticity of unfilled orders to GDP will be higher in expansions than in downturns. Table (2.15) shows these elasticities estimated from the model along with their data counterparts. The model does an outstanding job at replicating the difference in elasticities between the two states.[33]

Slow recoveries

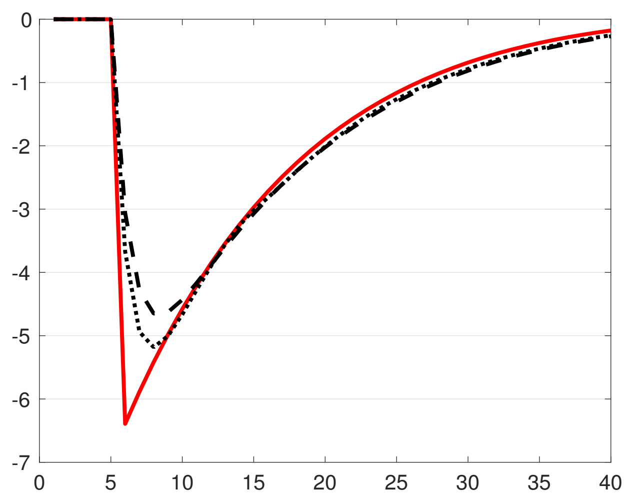
[33]The only caveat is that the model generates a negative elasticity of unfilled orders to GDP when the economy is below trend. However, the changes in magnitude of the elasticities are fairly accurate.

Figure 2.15: Asymmetric response of investment

(a) Positive productivity shock



(b) Negative productivity shock



Notes:Impulse response functions to positive innovations to the productivity process. Responses are generated using the piecewise linear policy function obtained with the algorithm in Guerrieri and Iacoviello (2017), around a non-stochastic steady state. The responses correspond to the real value of shipments, this is, shipments of capital goods times the average price of unfilled orders.

Table 2.15: Elasticities with respect to GDP when GDP is above and below trend

Data	Ship		UFO	
	Above	Below	Above	Below
	1.74	2.5	3.01	1.19
Model	Ship		UFO	
	Above	Below	Above	Below
	1.45	2.49	3.82	-0.51

Notes: Elasticities are computed from HP-filtered data from the M3 survey. Model elasticities correspond are produced from HP-filtered data simulated for one thousand periods after discarding a 150 periods burn-in from the Financial Friction calibration. Simulations use a piecewise linear policy function around a steady state obtained with the algorithm of Guerrieri and Iacoviello (2017)

The non-linearities in the response of investment in the model can produce slower recoveries, relative to the Standard calibration. For large shocks, as the financing constraint binds, the producer accumulates more unfilled orders relative to shipments. The value of $\theta < 1$, the convex cost of turning started projects into work-in-process and the value of unfilled orders as collateral will deter the producer from turning unfilled orders into shipments rapidly. The producer sheds these unfilled orders through a longer period of time, carried in part by the momentum of having a delivery lag. In contrast, in the Standard calibration, shipments are always equal to new orders, there are no incentives to hold unfilled orders that can slow the recovery. Table (2.16) compares the number of quarters it takes for the response of investment in the Financial Friction calibration to catch-up with the response of the Standard calibration for different size of shocks. For a shock that decreases GDP by 2% at the trough, the difference in the recovery between the two models is negligible. As the shock increases the duration of the recovery increases dramatically. For a shock that brings GDP down by 4% at the trough it takes 12 quarters for the Financial Friction model to catch-up with the Standard model.

Table 2.16: Quarters until Financial Friction model catches-up to Standard model

GDP decline	Description	Quarters
2%	One standard deviation of GDP	0
4%	Comparable to Great Recession	12
6%	—	19

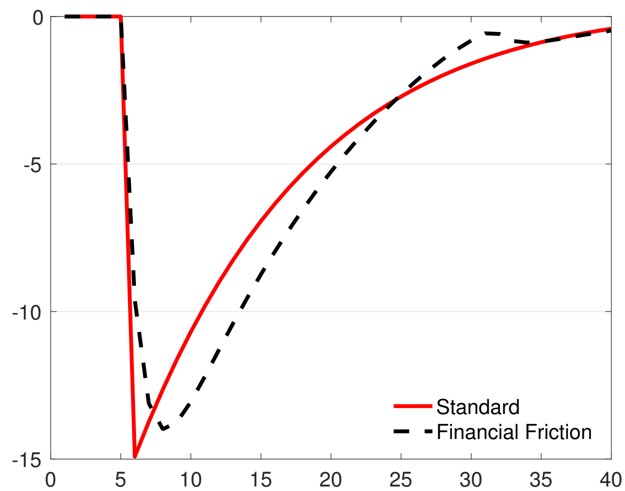
Notes: Quarters represents the number of periods after the through, that it takes for the response of investment under the Financial Friction calibration to cross the response under the Standard calibration. Responses are generated using the piecewise linear policy function obtained with the algorithm in Guerrieri and Iacoviello (2017), around a non-stochastic steady state. The responses correspond to the real value of shipments, this is, shipments of capital goods times the average price of unfilled orders.

The Great Recession

As a test of the importance of the mechanism for investment dynamics, I compare the responses of investment under both the Standard and Financial Friction calibration to a shock that produces a decrease in GDP to its trough comparable to the drop in the Great Recession. The fall of GDP from its peak in 2007q4 to its trough in 2009Q2 was 4.3%. Panel (a) of Figure (**??**) shows these responses. The drop at the trough is similar across the two calibrations, 14.9% in the Standard model and 13.9% in the Financial Friction one. The dynamics differ in a clear way, with the Financial Friction calibration producing a hump-shaped response. The cumulative response under the Financial Friction calibration is 67% bigger than under the Standard one. In part, this follows from the slower recovery of the former, taking 16 quarters to catch-up to the response under the Standard calibration. In essence there are significant differences in investment dynamics for large enough shocks. These differences are able to explain investment slumps after important crises. For comparison Panel (b) shows the cyclical component of investment during and after the great recession. Investment presents a hump-shaped response that drops almost 22% at its trough, larger that my results for either calibration. The recovery, from through to its level of 4% above trend before the steep drop, takes 11 and 20 quarters. This is similar to what the model predicts.

Figure 2.16: Response of investment to a Great Recession shock

(a) Model response of investment



(b) Cyclical component of investment in the data

Notes:Responses are generated using the piecewise linear policy function obtained with the algorithm in Guerrieri and Iacoviello (2017), around a non-stochastic steady state. The responses correspond to the real value of shipments, this is, shipments of capital goods times the average price of unfilled orders. Data on investment corresponds to hp-filter log-investment. Investment is the series on Real Gross Private Domestic Investment from the BEA

2.8 Conclusion

In this paper I have described some important features of the cyclical behavior of shipments and unfilled orders of capital goods producers. Mainly, their behavior is state-dependent: the elasticity of shipments with respect to GDP is higher during downturns and the opposite is true for the elasticity of unfilled orders. This behavior can be explained by the introduction of financial frictions. I show in the data that capital producers that face financial constraints, as they would in a downfall, respond to new orders by increasing shipments less than an unconstrained firm and increasing unfilled orders more than the unconstrained counterpart. In a downfall the fall of new orders makes shipments of capital goods fall more than they would without the financial friction, increasing the elasticity of shipments with respect to GDP and decreasing the elasticity of unfilled orders. This is exactly the behavior we see in the data. I calibrate a quantitative dynamic stochastic general equilibrium model that incorporates delivery lags in capital goods production and the financial friction as occasionally binding constraints. I show that accounting for this state-dependence is important to understand the dynamics of investment during downturns and recoveries. As an application, following a negative shock that decreases GDP as much as in the Great Recession, the model produces a cumulative fall of investment 67% higher than the response in a standard RBC model. The recovery is also slower in the model with the financial friction, where the response of investment takes 16 quarters to catch-up with the response generated by the standard RBC model.

Chapter III

What Inventory Behavior Tells Us About Changes in the Price Markup

(with Andrew D. Usher)

3.1 Introduction

The increase in market concentration in several industries through the second half of the twentieth[1] century has brought the literature to pay close attention to many of the changes that may accompany this. For example, *Gutierrez and Philippon* (2018) point to this as a possible culprit for under investment. *Autor et al.* (2017) study the fall in the labor share resulting from increasing concentration due to heterogeneous productivity. The question of the degree of market power that firms hold because of this concentration is still open and the price markup, defined as the ratio between sale price and marginal cost, provides away to start answering it.

Given the difficulty to acquire good quality price and marginal cost information, economist have resorted to estimate the price markup through several methods, making use of equilibrium and firm's optimization conditions. One of the favored method-

[1] See for example *Gutierrez and Philippon* (2018)

ologies when estimated the markup for several industries is based on *Hall* (1988) and makes use of the first order condition of the firms variable cost minimization problem. Notably, recent work by *Loecker et al.* (2020) used this result, along with balance sheet firm data, to estimate the change in the economy-wide markup since the 1960's. In their results, they find that the price markup may have rise by as much as 60%. This finding, has sparked big interest in the topic because of the implications that a change of this magnitude would have.

Basu (2019) pointed out a concern with this estimation. A change in the price-markup of the magnitude found by *Loecker et al.* (2020) should be accompanied by significant changes in the economy which are not aparent. Albeit, no estimation method is perfect and using the cost minimization first order conditions may have shortcomings. Mainly, the costs used in estimation should correspond to variable inputs of production. Two problems arise with this assumption, first, the way firms keep their accounting records of cost may vary significantly. Having firms report some overhead fixed costs as cost of production when others may not. Second, some inputs used in production may not correspond to the cost of goods sold if the firms holds down inventories.

In this paper we look to contribute to the debate by looking at the change in price markup through a different first order condition. Based on *Bils and Kahn* (2000) we consider the problem of a firm that must hold inventories to produce sales. The first order condition of the firm ties down the price-markup to the ratio of the stock available to sales, an important statistic in the literature of inventories. Intuitively, the cost to the firm of missing a sale is given by the markup. In times when the markup is higher, the firm will want to hold larger quantities of inventories. This way, the stock to

sales ratio, which is readily available from balance sheet data, provides information on the changes of the price markup.

In addition to the stock to sales ratio, our first order condition includes the expected growth rate of marginal cost. We use balance sheet data to estimate the firms production function to back out total factor productivity. This variable reflects both technology and input price changes and can be used to forecast the firm's marginal cost growth. Our first order condition, allows us to remain agnostic to changes in prices or market structure and the actual breakdown of the cost of production.

In our estimation, we find that the stock to sales ratio, accounting for changes in the productivity of the stock is decreasing through the entire period, as previously documented in the literature[2]. However, the firms discounted marginal cost growth increases through time, due to a decreasing discount rate and a relatively flat marginal cost series. The combination of these factors point towards a slightly decreasing markup, with a fall of around 5% between 1970 and 2018. Most of the fall happens throughout the 70's and 80's decades and the series becomes relatively flat starting in the 2000's.

Two factors lead to the conclusion of falling markups. First, the falling stock to sales ratio reflects a smaller loss of the firm when a sale is not produced. This remains true even when adjusting for the increase in the productivity of the stock to produce sales. Second, the falling discount rate implies a falling cost of carrying inventories which should make the firm more willing to hold stock in order to produce sales. Our conclusion from this results is that further study of the importance of firm dynamics are necessary in order to understand the changes in the price-markup. Static first order conditions, while convenient, appear to be missing important information given

[2] see *McConnell and Perez-Quiros* (2000)

the changes in the dynamic variables of the firms problem, the stock available and the discount rate.

The structure of the paper is as follows: In Section 2 we present a theoretical framework in which firms hold a stock of the final good in order to produce sales and smooth the cost of production. Section 3 presents the methodology and results of the estimation of the adjusted stock to sales ratio and discounted expected growth in marginal cost. In section 4 we use the estimated series to back the changes in the price markup. Section 5 presents conclusions.

3.2 Theoretical framework

In this section we develop a model similar to *Bils and Kahn* (2000) in which firms hold inventories to facilitate sales. This is the current consensus reached in the literature, as it explains procyclical inventory investment. Inventories, or more specifically, the available stock, can facilitate sales by, for example, preventing stockouts or allowing to match products with costumers. [3]. In our model sales of the final good consist of successful matches between consumers and the available stock, a_t. The firm chooses both the available stock and price p_t before matching happens and after observing the aggregate state of the economy Θ_t. Given the stock, price and the aggregate state, consumers search for the product with an intensity $0 \leq d(p_t, \Theta_t) \geq 1$. Sales are determined by a matching function given by

$$s_t(p_t, a_t; \Theta_t) = d(p_t; \Theta_t) a_t^{\phi_t} \tag{3.1}$$

[3]For a broader discussion of inventory investment behavior see for example *Wen* (2005).

By construction $s_t \leq a_t$. The time-varying parameter $0 < \phi_t \leq 1$ is the elasticity of sales with respect to stock and represents how essential the stock available is to successfully match with consumers. To understand the nature of this parameter consider the perfect competition example where

$$d(p_t; \Theta_t) = \begin{cases} 1 \quad if \quad p_t = p_t^* \\ 0 \quad if \quad p_t \neq p_t^* \end{cases} \tag{3.2}$$

In this case, consumers will buy the product at the market price as long as they are successfully matched with it. Matching will only depend on the stock available. Consider two types of firms, the first firm has a fixed share of the stock across its stores. The second firm has a distribution network between its stores, allowing to move stock where necessary. Even if both firms produce the same stock a^*, the second firm will reach more consumers facilitating matches and sales, this is captured by a higher level of ϕ_t. The time variation in ϕ_t is due to changes in distribution and inventory management technology through time.

Let y_t be the level of production of the final good at a cost given by the function $C(y_t; \omega_t)$ where ω_t represents the realization of the firms idiosyncratic productivity. The stock available evolves according to

$$a_t = a_{t-1} - s_{t-1} + y_t \tag{3.3}$$

With the matching function 3.1 and assuming both aggregate state and productivity processes are first order Markov, the solution to the the profit maximization problem of the firm satisfies the following Bellman Equation subject to 3.1 and 3.3

$$V(a; \Theta, \omega) = \max_{p,a'} \{ps - C(y; \omega) + E[\beta V(a'; \Theta', \omega')]\} \tag{3.4}$$

Here β represents the realization of the stochastic discount factor. Let c_t be the marginal cost of production of the firm in period t. Combining the first order condition $\partial a'$ with the Benveniste-Scheinkman envelope equation for the state a, we get Equation 3.5

$$1 = \phi_t \frac{s_t}{a_t}\frac{p_t}{c_t} + \left(1 - \phi \frac{s_t}{a_t}\right) E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] \tag{3.5}$$

The first order condition with respect to price is given by

$$1 = \xi_t p_t E\left[1 - \beta_{t+1}\frac{c_{t+1}}{p_t}\right] \tag{3.6}$$

Where ξ is the price elasticity of the search intensity function $d(p_t;\Theta_t)$. Notice that the search intensity function $d(p_t;\Theta_t)$ appears in equation 3.5 only through the ratio of sales to the stock available $\frac{s_t}{a_t}$, which is observable in the data. Focusing on equation 3.5 allows us to remain agnostic to the shape of $d(p_t;\Theta_t)$, meaning equation 3.5 remains valid under any type of market structure that can be modeled in this way. This includes the cases of perfect competition and monopoly.

The derivative of sales with respect to the stock available is $\phi_t \frac{s_t}{a_t}$ so we can rearrange equation 3.5 as follows to get an interpretation. At the optimal choice of a_t a perturbation Δa_t must be such that the change in costs equals the change in revenue,composed by the fraction of Δa_t sold at a price of p_t and the fraction kept in inventory with a shadow value of $E\left[\beta_{t+1}c_{t+1}\right]$.

$$c_t \Delta a_t = \frac{\partial s_t}{\partial a_t}\Delta a_t p_t + \left(1 - \frac{\partial s_t}{\partial a_t}\right) E\left[\beta_{t+1}c_{t+1}\right]\Delta a_t$$

Using equation 3.5 we can study changes in the price markup through the changes in the other firm-level variables connected to it. Solving for $\frac{p_t}{c_t}$ yields

$$\frac{p_t}{c_t} = \frac{1}{\phi_t}\frac{a_t}{s_t} - \left(\frac{1}{\phi_t}\frac{a_t}{s_t} - 1\right) E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] \tag{3.7}$$

Lets assume that marginal cost is constant (or decreasing) through time, so that $E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] < 1$. In that case the equilibrium markup holds a strictly positive relation with $\frac{1}{\phi}\frac{a_t}{s_t}$. The markup is the forgone benefit when a match fails hence, in times when the markup is high, the firm wants a higher stock relative to sales in order to successfully match. Additionally, changes in technology represented by ϕ_t affect the relation between the stock to sales ratio and the markup. At a given markup, if ϕ_t becomes higher, meaning the firm is better at converting stock into sales, the firm will hold a lower stock.

As we can see, the changes in markup in the last four decades can be inferred by the changes of these three variables, the stock-to-sales ratio, the expected change in marginal cost, and the elasticity ϕ_t. In the following section we will look at the historical behavior of this variables and work our way to the implication for the price markup.

3.3 Historical look of the firms' production

In this section we use annual firm level data from Compustat for the period between 1970 and 2017, to recover or estimate the variables connected to the price markup. We assume the firm has a production technology that takes variable inputs, L and capital, K given by

$$Y_{it} = e^{\omega_{it}} L^{\alpha_j^L} K^{\alpha_j^K} \tag{3.8}$$

The production function parameters vary by industry as classified by two digits

NAICS codes. There is no constraint on returns to scale through the parameters, we allow them to take any positive value.

3.3.1 Firm's forecast of marginal cost growth

The last term in equation 3.7 is the expected growth of discounted marginal cost for the firm. We take the stance of modeling this as a forecast made by the firm with the information available until the moment of the forecast. Two components enter these value, the stochastic discount factor and the growth rate of marginal cost. For a given stock-to-sales ratio, the price markup is decreasing in both of them. If marginal cost is higher in the future, the firm will choose to keep a higher stock for cost-smoothing purposes, even if the markup is high.

We assume that for the forecast, the firm treats the stochastic discount factor and the marginal cost growth rate as independent so that

$$E\left[\widehat{\beta_{t+1}\frac{c_{t+1}}{c_t}}\right] = E\,[\hat{\beta}_{t+1}]E\left[\widehat{\frac{c_{t+1}}{c_t}}\right] \tag{3.9}$$

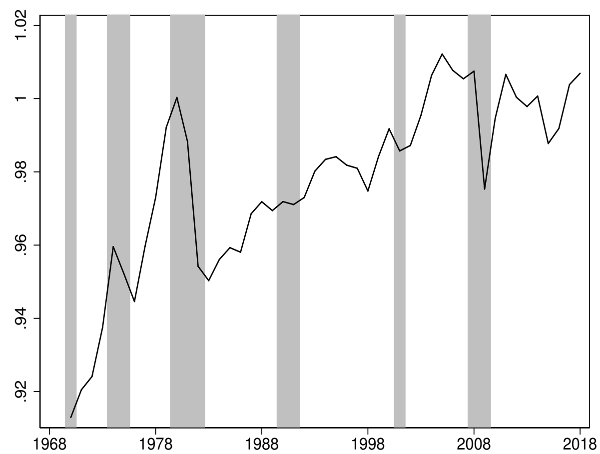
A firm forecasts the stochastic discount factor through its current financing cost, r_t^f. Simply put, we assume the firm chooses to discount future values using its time cost of funds. We compute real financing costs, as the ratio between "Interest and related expenses" and the firms total debt minus inflation[4]. Figure 3.1 shows in panel (a) the average $\beta_t = (1 + r_t^f)^{-1}$, weighted by sales, from 1970 to 2018. Notably, financing costs have steadily declined through these five decades to the point where the financing rate is below inflation. On average, for the last few years in our sample, the average financing rate is about half a percentage point lower than inflation. As

[4] Inflation is obtained through the GDP deflator

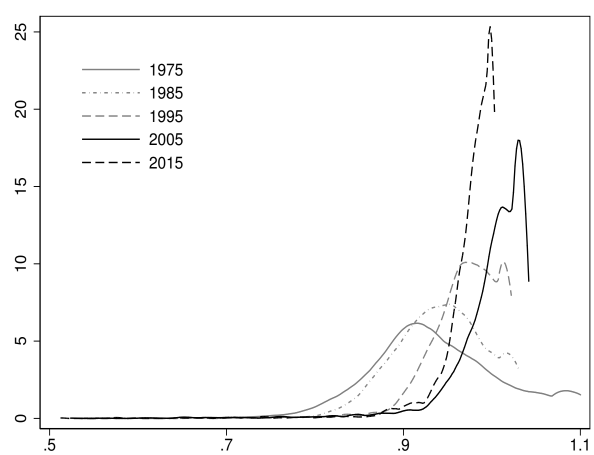
a result, the discount factor used by the firm has increased mostly increased during this period, with a few sharp declines corresponding to major recessions, as indicated by shading.[5]. Starting in 2004, the discount rate has been often above one, reflecting a financing rate below inflation.

Figure 3.1: Firms real discount factor from financing costs

(a) Sales-weighted average



(b) Firm distribution



On panel (b) of Figure 3.1 we show estimated densities for the distribution of discount factor (x-axis) across firms. In 1975, the density is almost centered a little above 0.9 while for 2005 and 2015 most of the mass has shifted towards higher values.

[5]A year is shaded if the economy was in recession for at least one quarter according to NBER recession dates.

The quick take of this graph is that the financing rates of all firms in the sample have decreased in this period as opposed to just the average rate. Further, the dispersion in rates has decreased as well, meaning most firms access similar lower rates.

The second component of the firm's forecast is the expected growth rate of marginal cost. Given the production function 3.8, marginal cost for firm i in industry j at time t is given by

$$c_{it} = e^{-\omega_{it}} \left(\frac{P^L_{it}}{\alpha^L_j}\right)\left(\frac{P^K_{it}}{\alpha^K_j}\right) \tag{3.10}$$

As mentioned above, L represents variable inputs rather than just labor. We assume that for the firm forecast, only productivity is expected to change from the current year. This is, $E\left[P^L_{it+1}\right] = P^L_{it}$ and $E\left[P^K_{it+1}\right] = P^K_{it}$. Implicitly, we are also assuming that the firm considers its forecasts for productivity and input prices to be independent, so we treat them as multiplicatively separable through the expectation operator. Under these assumptions we have that

$$E\left[\frac{c_{t+1}}{c_t}\right] = E\left[e^{\omega_{it}-\omega_{it+1}}\right]$$

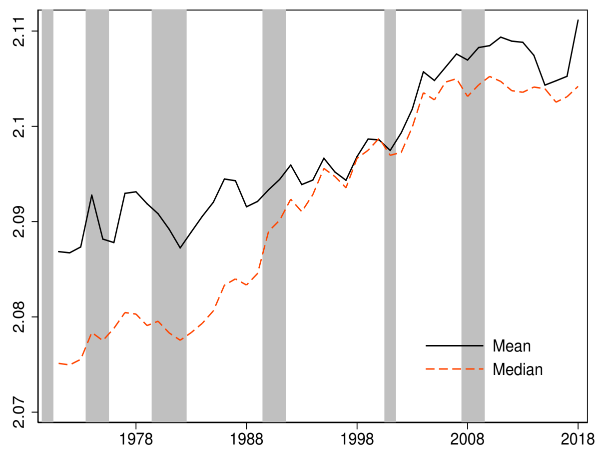
We follow the procedure in **?** to estimate the parameters of the production function by industry. We recover the values of productivity as

$$\hat{\omega}_{it} = (y_{it} - \hat{\varepsilon_{it}}) - \hat{\beta_j}^K K_{it} - \hat{\beta}^L_j P^L_{it} L_{it} \tag{3.11}$$

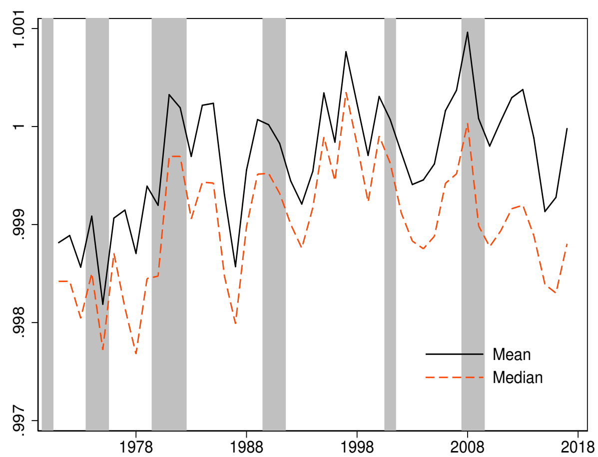
Let FGI_{it} be the final good inventories at the end of year t. The stock available is $a_{it} = s_{it} + FGI_{it}$. Combining this with equation 3.3 we can compute production $y_{it} = s_{it} + FGI_{it} - FGI_{it-1}$. The correction term $\hat{\varepsilon}$ corresponds to the estimated error from the first stage of the ACF procedure. We use "cost of goods sold" for the value of $P^L_{it} L_{it}$. Panel (a) of Figure 3.2 shows the sales-weighted average and median of our estimated productivity series. The productivity series increases steadily through the period of our sample. However, for both average and median, the total increase in the period is very modest, at around one percentage point. This points towards a flat series of expected growth in marginal cost. There is no evident cyclical behavior in the productivity series.

Figure 3.2: Firm's forecast of productivity and marginal cost growth

(a) Sales-weighted average productivity



(b) Sales-weighted average marginal cost growth

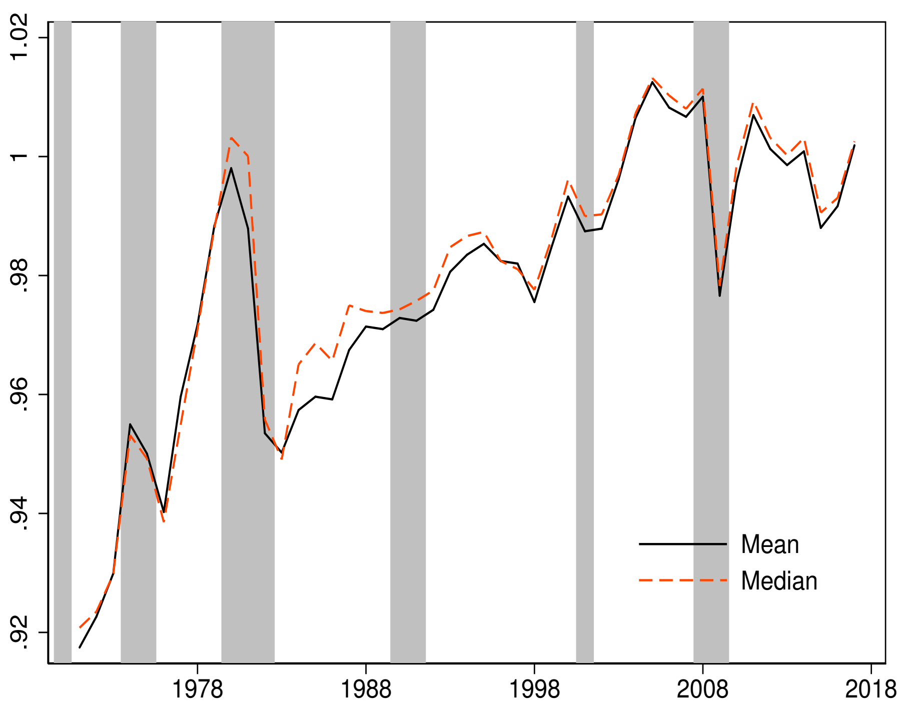


Having the productivity series $\hat{\omega}$, we build a forecast of marginal cost with a second order polynomial regression with firm and year fixed effects. The estimated equation is given by

$$c_{it+1} = \gamma_i + \gamma_t + \rho_1 c_t + \rho_2 c_t^2 + u_{it+1} \tag{3.12}$$

We follow *Blundell and Bond* (1998), instrumenting with lag-differences of the dependent variable. Panel (b) of Figure 3.2 shows the sales-weighted average and median of the estimated growth in marginal cost. As foreshadowed by our productivity series, the estimate for expected marginal cost growth is very flat through the entire period. Figure 3.3 shows the estimated series of discounted expected marginal cost growth. The contribution of the discount factor β dominates, making the series steadily increasing through the period. This result provides the first component of our markup estimation. From equation 3.7 we have that, holding everything else constant, the markup is strictly decreasing in the discounted expected marginal cost growth. Our result in this section puts pressure towards a decreasing markup in our sample period.

Figure 3.3: Firm's forecast of expected discounted growth in marginal cost



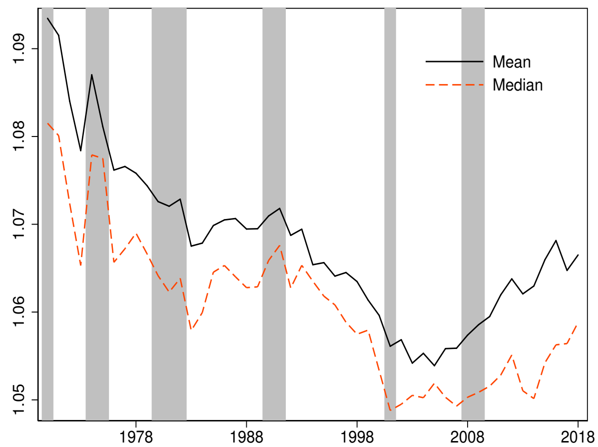
3.3.2 Stock-to-sales ratio

The next component in our markup estimation is the ratio between the available stock and the sales of the production good. This variable holds the key intuition of this paper. If markups are increasing, the loss faced by the firm from a stockout is also increasing. Everything else constant, a firm will increase the available stock relative to sales to prevent stockouts as they become costlier. Figure 3.4 shows the sales-weighted average of the ratio for all industries on panel (a). Consistent with the literature, the ratio falls from the seventies and through the great moderation, reaching a through in the mid-2000's. There is a modest recovery of the ratio in the last decade of the sample, the period after the great recession. In panel (b), we show that this behavior is not present in all industries. In the case of retail and wholesale trade, there is no obvious decline in the ratio. These are industries with higher dependence on inventories, as evidenced by the larger average value and volatility of the ratio when compared to the rest of the economy.

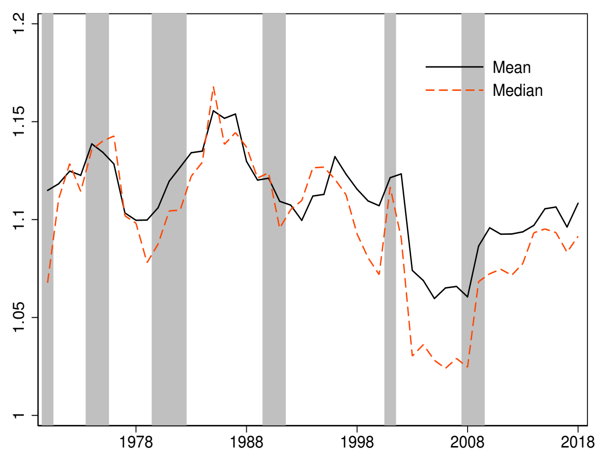
Equation 3.7 shows a positive relation between the markup and the ratio of available stock to sales as long as $E\left[\beta_{t+1}\frac{c_{t+1}}{c_t}\right] < 1$. Figure 3.3 shows that this is the case on average in our data up until 2003. From 2004 onwards, our data suggests a negative relation between the markup and stock to sales ratio. This point to a markup that should be decreasing through the entire sample period, if every other component in equation 3.7 is held constant. However, in the case of retail and wholesale trade, the industries for which are model should fit best, we do not see this obvious decline of the ratio. Additionally, it is still necessary to look at was has happened to ϕ, the technology that allows firms to turn available stock into sales.

Figure 3.4: Ratio of available stock to sales

(a) All industries



(b) Retail and wholesale



3.3.3 The elasticity of sales with respect to available stock

In this part we estimate the elasticity of sales with respect to available, ϕ. We estimate the following specification as in *Blundell and Bond* (1998), instrumenting with lagged differences of the variables to correct for bias in the autoregressive coefficient.

$$ln(a_{it}) = \gamma_i + \gamma_t + \rho ln(a_{it-1}) + \frac{1}{\phi} ln(s_{it}) + u_{it} \tag{3.13}$$

Table 3.1 shows the estimated values for the entire period in the first column. Our estimate of *phi* for the entire sample is around 0.85. Lower values of *phi* mean that the firm requires a higher stock available to produce sales. Given this value of ϕ even under a setup in which consumers are always willing to buy the good at market price $d(p_t^*) = 1$, as in the example in Section 2, a firm with a stock of a will be left with $a^{0.85}(a^{0.15} - 1)$. As ϕ approaches 1, the firm does not require inventories to make a sale, however, a monopoly firm can still choose to carry inventories by choosing p_t so that $d(p_t) < 1$. From equation 3.7 we can see that increasing ϕ increases the importance of the marginal cost ratio for the markup. This is because as the firm stops requiring inventories to produce sales, it can use inventories to smooth costs of production through time.

Table 3.1: Dynamic panel estimates of the elasticity of sales to stock available

	Full sample	pre 2000	post 2000
ρ	-0.17	-0.46	-0.12
	(0.06)	(0.46)	(0.04)
$\frac{1}{\phi}$	1.18	1.47	1.12
	(0.06)	(0.46)	(0.04)
Obs.	87,523	45,755	41,768

The second and third columns show estimates of ϕ, dividing the sample before and after the year 2000. For the first period, from 1970 to 1999, the estimate of

ϕ is around 0.68. For the second part it increase to about 0.89. This is consistent with the changes in distribution and sales technology of the past decades. The need of the firm to hold inventories to produce sales has decreased considerably. Firms need lower ratios of stock available to sales, everything else equal. For example, a firm that wanted to sell 2 units before 2000 would need an available stock of 2.77 units, delivering a ratio of available to sale of 1.39. After the year 2000, the stock available required to sell 2 units is 2.17 and the ratio 1.09. This increase in ϕ allows to accommodate the decrease in the stock to sales ratio even if markups were increasing.

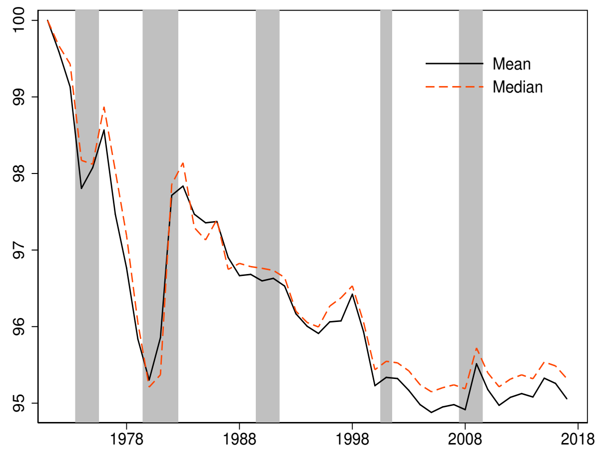
3.4 The price markup

Following equation 3.7 we estimate the change in the markup through our sample with the variable estimates from the previous section. We split the value of ϕ as estimated, inputting one value for firms before the year 2000 and another one afterwards. Figure 3.5 shows the estimated markup considering both a change in ϕ (panel (a)) and holding it constant (panel (b)). In both cases we see a mild decrease in the markup over the period. Considering a change in ϕ the markup decreases about 5% and becomes relatively constant starting in the 2000's. With a constant ϕ the drop is weaker of about 2.5% points. These are the results of a decreasing stock to sales ratio combined with a ratio of marginal cost thats both increasing and less than unity for most of the years in our sample. After, the ratio of marginal cost becomes higher in the 2000's we see a markup that starts slightly recovering.

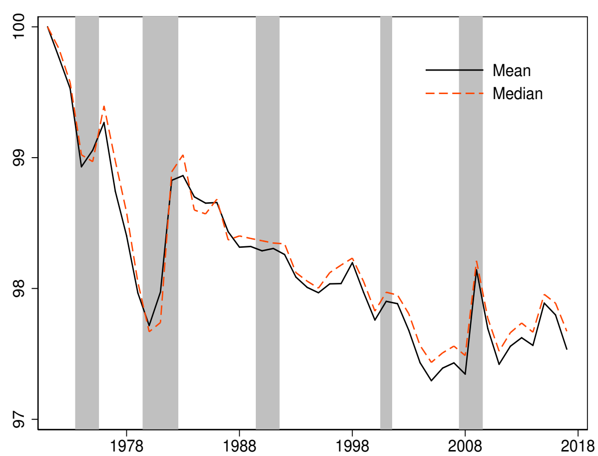
The fact that the discount rate of the firm decreases steadily produces an increasing discounted marginal cost growth. It is cheaper for firms to hold inventories as the rate goes down, making it relatively cheaper to produce presently. The decreasing cost of holding inventories together with the decrease in the stock to sales ratio

Figure 3.5: Changes in price markup, index

(a) One change in ϕ



(b) Constant ϕ



implies that the relative cost to the firm of loosing a sale is decreasing, leading to the conclusion of a falling markup.

3.5 Conclusion

The theoretical framework of our paper shows that some of the firm's dynamic variables play an important role when determining the price-markup. If the firm is able to hold inventories, the change in the discounted marginal cost of production in the future becomes relevant for the firms decision to sell at a certain price. If the discounted marginal cost of production is increasing, the firm can hold on to sell presently and accumulate stock of the final good. However, firms in the sample are constantly reducing the relative stock of final goods. This fact, follows partially from lower need to hold stock in order to produce sales, as distribution and inventory technology has become better. This last fact is not enough to rationalize the fall in the relative stock, meaning that additionally, the cost to the firm of loosing a sale must be decreasing, at least slightly. This cost is reflected by the price-markup, as a firm looses this value when failing to complete a sale. The historical behavior of both stock and discounted marginal cost are hard to reconcile with a scenario in which markups are increasing. If markups are indeed growing, further work on the firm's dynamic problem is necessary to understand the puzzling behavior of the stock and cost.

Chapter IV

Inventories Today: Stock-Out Prevention vs Production Smoothing

4.1 Introduction

The inventories to sales ratio is a key variable to understand the firm's intertemporal behavior. This ratio is countercyclical, which along with procyclical inventory investment[1], has led to a literature consensus that inventories are necessary to produce sales. For example, inventories used to prevent stockouts or to match consumers with products. As noted by *Wen* (2011), procyclical inventory investment follows from the need of firms to build up a stock in order to produce sales during booms. As marginal cost of production grows in a boom, inventory accumulation fails to keep up with sales one-for-one, leading to a countercyclical ratio.

There are, however, important changes in the inventories to sales ratio throughout the second half of the twentieth century. First, there has been a steady decline in the inventories to sales ratio starting in the 1980's. This fall has been interpreted as a consequence of better distribution and inventory management, as argued in *McConnell and Perez-Quiros* (2000). As the importance of inventories to produce sales

[1] At mid frequencies. Inventory investment is countercyclical at high frequencies

falls the incentives for firms to hold inventories can be driven by other factors, such as cost smoothing or as a separate form of investment.

Second, I document that the correlation between inventory investment and capital investment has steadily decreased through the same period. Intuitively, when firms required inventories in order to generate sales, both investment in capital and in inventories are complements in the production of sales. In times when capital investment is high, inventory investment is also high. As the importance of inventories to produce sales declines, the firm can choose to hold inventories to smooth the cost of production. An increase in inventories becomes an input for future sales. In this sense, inventory investment and capital investment become substitutes in the production of future sales as neither is essential when the other is present. Firms with a large stock of final good inventories may choose to delay capital investment while they can deplete their stock. Firms that are undertaking a capital investment project may deplete their current inventory stock as future production will increase. The decrease in correlation not only provides some evidence in favor of inventories loosing importance to produce sales but also may point to a mechanism through which inventory holdings affect aggregate capital investment.

To analyze the mechanism behind these changes I extend the stockout prevention model of *Wen* (2011) to allow for improvements in distribution technology. I calibrate the model so that the improvement in distribution technology allows to match the fall in the inventory to sales ratio. This calibration produces a weakening correlation between inventory and capital investment that matches the data. Further, in the model the change in distribution technology leads to a fall of 12% in the volatility of capital investment relative to GDP. This finding is consistent with a world in which firms choose either inventory investment or capital investment to increase their future production instead of doing it by capital investment alone.

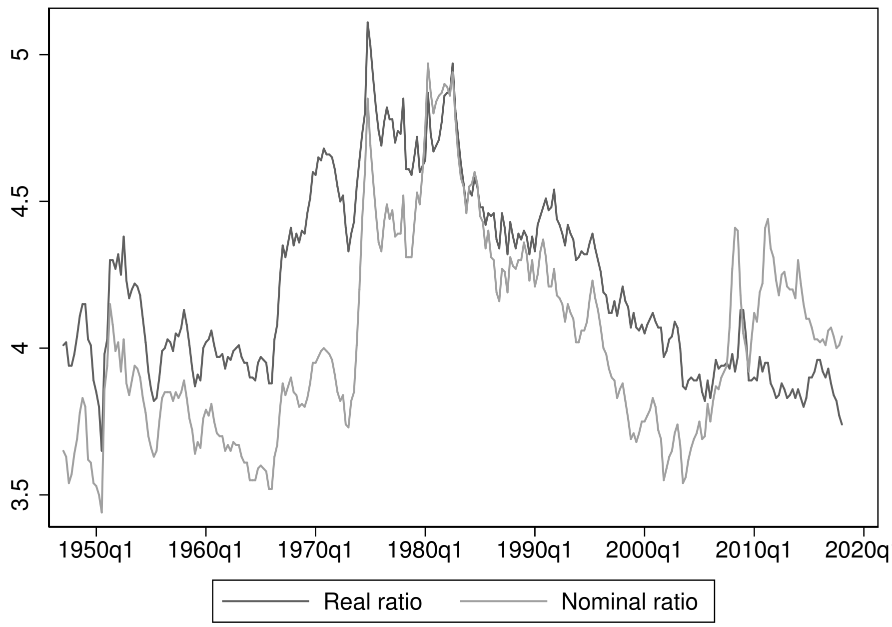
4.2 Historical changes in inventory variables

I begin by documented two empirical facts from the second half of the twentieth century: a fall in the inventories to sales ratio and a weakening correlation between inventory and capital investment. Figure 4.1 shows data on the final good inventories to sales ratio from the Bureau of Economic Analysis. The lighter line corresponds to the raw ratio of total value of final good inventories over sales and shows a consistent decrease starting in the 1980's until the second half of the 2000's. The darker line corresponds to the ratio adjusted for changes in cost of production [2]. The real ratio shows a similar behavior except that the series continues decreasing in both decades after 2000. To understand the magnitude of this drop, consider the following, a ratio of 5, as the one in 1974, means the firm holds 5 quarters, in terms of sales, of final good inventories. Then the size of the fall can be seen as more than one quarter of sales, as the ratio is below 4 at the end of the sample. Given the size of the fall, it is plausible that other economic aggregates are affected by these changes. In general, the literature has tried to tide this change with the Great Moderation, however, I take the more specific task of looking at the effects it has on capital investment.

In the next step, I look at the relation between inventory and capital investment through the period. Figure 4.2 shows the evolution of the across-firm correlation between inventory investment and the capital investment rate between 1975 to 2011. At the beginning of the sample, the two variables have a positive relation, firms with high inventory investment also have high capital investment. By the end of the pe-

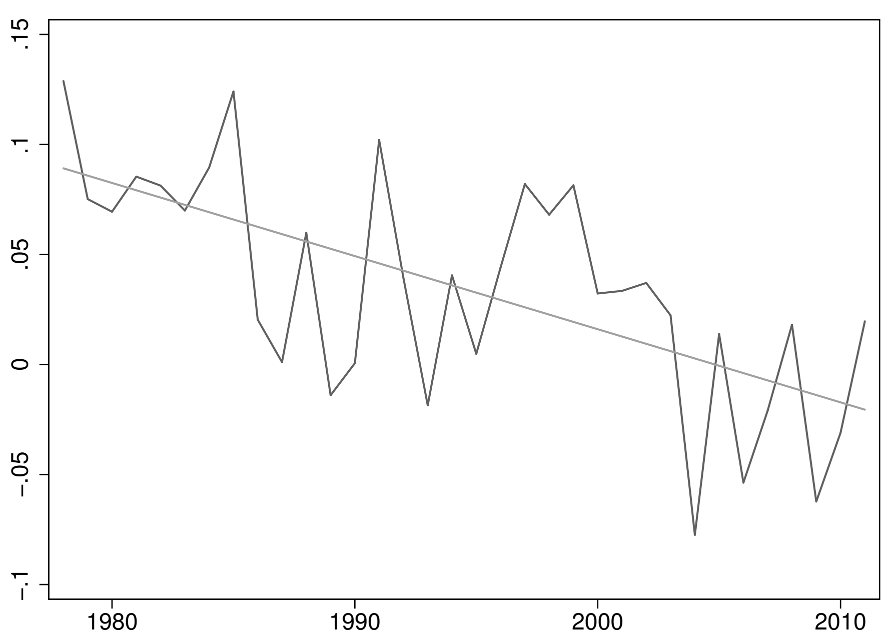
[2] Both data series are from NIPA tables from the Bureau of Economic Analysis. The ratio is adjusted by cost of production to account by firms reporting the value of inventories as cost of production rather than price

Figure 4.1: Ratio of total inventories to sales of final goods



riod, the positive relation has vanished, tilting slightly towards a negative correlation: firms with high capital investment have low inventory investment.

Figure 4.2: Correlation between the capital investment rate and change in inventories



Relating the fall in the inventories to sales ratio to the weakening correlation between inventory and capital investment requires a theoretical framework. The way this two may be linked is exemplified by this thought experiment

1. Improvement in distribution technology leads to a fall in the ratio

2. Firms stop holding inventories to produce sales and star holding them to smooth the cost of production

3. In the presence of persistent demand shocks, a firm increases current and future sales. The way they do it will differ depending on why they hold inventories.

    - Inventories produce sales: firm increases inventory investment to increase current sales. Firm increases capital investment to increase future sales.

    - Inventories to smooth costs: Firm increases inventories to substitute future production for current production. Capital investment is an input for future production, then substituting future production for current production will substitute capital investment for inventory investment.

In the next section, I use a theoretical framework in which firms can hold inventories to produce sales and to smooth the cost of production. The model allows for improvement in distribution technology that makes inventories less essential to produce sales. This allows me to analyze whether the weakening correlation between capital and inventory investment can be explained by the improvement in distribution technology.

4.3 Model

In this section I extend the stockout prevention model of **??** to allow for improvements in distribution technology. The stock of the final good is distributed in different locations before local demand for the good is realized. This creates a stockout prevention reason for holding inventories that will be weakened as firms develop distribution technology.

4.3.1 Household

The economy is comprised by one large household that consumes the final good in a unit measure of different locations. Consumption of the good in location i is labeled $c_t(i)$ and its subject to a location specific demand shock $\theta_t(i)$. I assume the shocks to be idiosyncratic, independent and identically distributed across time and locations. The household makes orders in each of the different location, $y_t(i)$ at a price normalized to 1, before the realization of $\theta_t(i)$. The household can hold a stock of the good in every location $s_t(i)$ which depreciates at a rate d. Additionally, there is an amount of the good X_t in a distribution center that can be send to the different locations after the realization of the idiosyncratic shocks. These late orders are labeled $x_t(i)$ and come at a price $1 + \eta$. If $\eta = 0$ the household will restock the different locations after observing the realization of $\theta_t(i)$, eliminating the need for inventories to generate consumption. Figures, 4.3 and 4.4 show the different steps in distribution before and after the realization $\theta_t(i)$.

The law of motion for the stock of the good in location i is given by Equation 4.1. If $\eta = 0$ then $y_t(i) = 0$, $s_t(i) = 0$ and $x_t(i) = c_t(i)$. The stock to sales ratio is given by $s_t(i)/c_t(i)$ and will decrease towards zero as η decreases. The household provides labor N_t for the production of the final and receives a wage rate w_t. Additionally, it can hold a single type of bond B_t which pays a risk-free rate r_t. The household budget constraint is given by Equation 4.2

$$c_t(i) + s_t(i) = (1 - d)s_{t-1}(i) + x_t(i) + y_t(i) \tag{4.1}$$

Figure 4.3: Distribution before the realization of $\theta_t(i)$

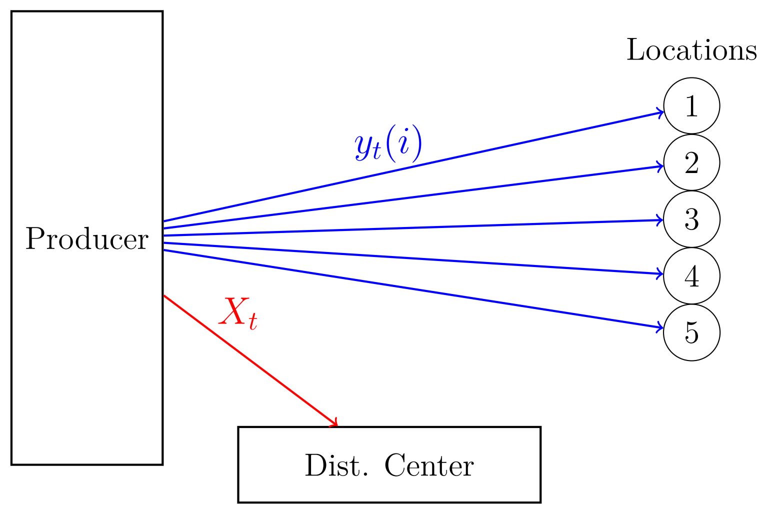
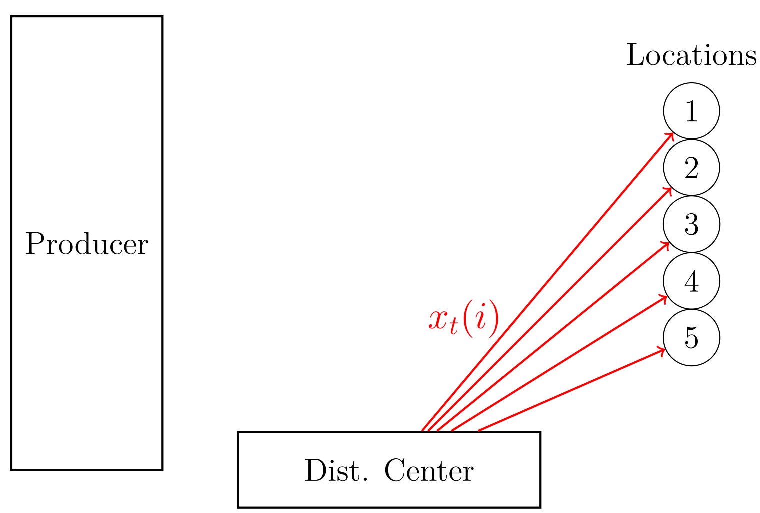


Figure 4.4: Distribution after the realization of $\theta_t(i)$



$$\int_0^1 y_t(i) + (1+\eta)x_t(i)di + B_{t+1} = (1+r_t)B_t + w_t N_t \tag{4.2}$$

The household chooses $y_t(i),\ x_t(i),\ c_t(i),\ s_t(i),\ N_t$ and B_{t+1} in order to maximize

$$E\sum\left(\beta^t \frac{\phi_t}{1-\sigma}\left[\int_0^1 \theta_t(i)c_t(i)^\rho di\right]^{\frac{1-\sigma}{\rho}} - \frac{aN_t^{1+\gamma}}{1+\gamma}\right) \tag{4.3}$$

subject to the law of motion of the stock in each location 4.1, the budget constraint 4.2 and nonnegativity constraints on $x_t(i)$ and $s_t(i)$. There is an aggregate demand shifter ϕ_t which generates aggregate uncertainty. Utility from consumption is CES across time and locations, with respective elasticities of substitution σ and ρ.

Let the multipliers on each constraint be $\lambda_t(i)$ (Equation 4.1), κ_t (Equation 4.2), $\pi_t(i)$ ($s_t(i) \geq 0$) and $\mu_t(i)$ ($x_t(i) \geq 0$). The first order conditions are given by

$\partial y_t(i)$:

$$\kappa_t = E_\theta \lambda_t(i) \Rightarrow E\lambda_{t+1}(i) = E\kappa_{t+1} \tag{4.4}$$

$\partial c_t(i)$:

$$\phi_t \tilde{C}_t^{1-\sigma-\rho}\theta_t(i)c_t(i)^{\rho-1} = \lambda_t(i) \tag{4.5}$$

$\partial x_t(i)$:

$$\lambda_t(i) + \mu_t(i) = [1+\eta]\kappa_t \tag{4.6}$$

∂B_{t+1}:

$$\kappa_t = \beta E(1+r_{t+1})\kappa_{t+1} \tag{4.7}$$

∂N_t:

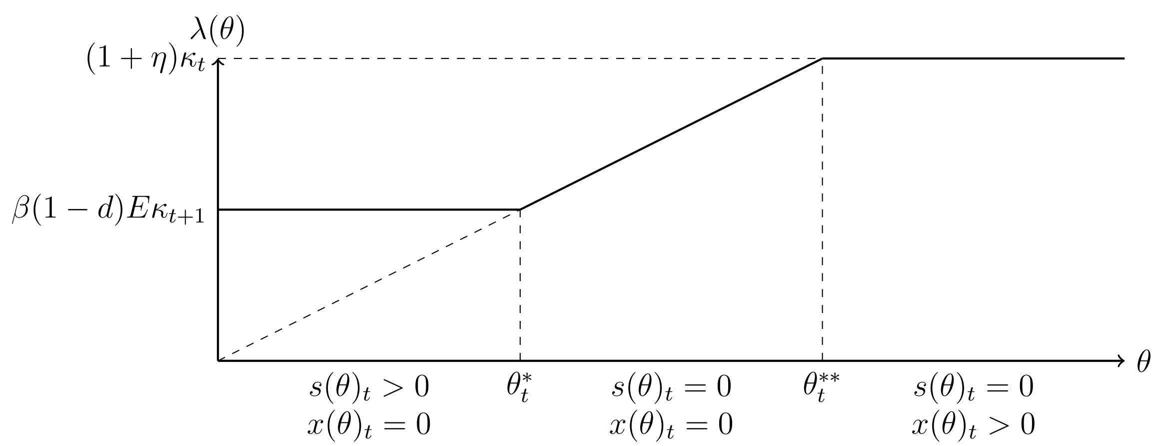
$$aN_t^\gamma = \kappa_t w_t \tag{4.8}$$

$\partial s_{t+1}(i)$:

$$\lambda_t(i) = \beta(1-d)E\kappa_{t+1} + \pi_t(i) \tag{4.9}$$

Before the realization of the idiosyncratic shocks, all locations are identical and the household will choose orders $y_t(i)$ in order to stock up on each location to the same quantity, T_t. The multiplier, κ_t is the shadow value of increasing the amount of the final good independently of which location it is stocked in. This shadow value depends only on the realization of the aggregate shock ϕ_t and not on the realization of the idiosyncratic shocks. The multiplier $\lambda_t(i)$ is the shadow value of a unit of the good in location i. A high realization of $\theta_t(i)$ makes the stock T_t small, relative to the desire for the good in location i. This brings the value of $\lambda_t(i)$ up, making an additional unit in this location more valuable. Without idiosyncratic uncertainty, $lambda_t(i) = \kappa_t$ for all locations i. This identity holds as well when $\eta = 0$ as we can see in Equation 4.6. Improvements in distribution technology have the same effect as reducing idiosyncratic uncertainty. Figure 4.5 shows the relation between $\lambda_t(i)$ and $\theta_t(i)$.

Figure 4.5: Regions according to the shock



As in *Wen* (2011) there is a cutoff $\theta_t(i) > \theta_t^*$ above which the household consumes all of the available good in location i remaining with $s_t(\theta_t(i)) = 0$. Below this cutoff, an additional unit of the good in location i will stay in inventory, making the value $\lambda_t(i) = \beta(1-d)E\kappa_{t+1}$. The ability to restock after the idiosyncratic shocks produces a second cutoff $\theta_t^{**} = \frac{(1+\eta)\kappa_t}{\beta(1-d)E\kappa_{t+1}}\theta_t^* > \theta_t^*$ above which the household makes additional orders $x_t(i) > 0$ to consume. The shadow value $\lambda_t(i) = (1+\eta)\kappa_t$ since the household could choose to stock after the idiosyncratic shock.

4.3.2 The firm

A representative firm produces the final good for all locations, taking both input and final good prices as given. The firm faces a cost of adjusting capital that depends on the deviation from the steady state level. The firm's problem is to choose capital and labor inputs in order to maximize

$$E\sum_{t=0}^{\infty}\left(\prod_{s=0}^{t}\frac{1}{1+r_t}\right)(AK_t^{\alpha}N_t^{1-\alpha} - w_tN_t - I_t - \frac{\chi\bar{K}}{2}(\frac{I_t}{\bar{K}}-\delta)^2) \tag{4.10}$$

subject to the capital law of motion

$$K_{t+1} = I_t + (1-\delta)K_t \tag{4.11}$$

with an associated Lagrange multiplier q_t, the shadow value of installed capital. The first order conditions are fairly standard and given by

∂I_t:

$$\frac{I_t}{\bar{K}} - \delta = \frac{1}{\chi}(q_t - 1) \tag{4.12}$$

∂K_{t+1}:

$$q_t = E\left[\left(\frac{1}{1+r_{t+1}}\right)(MPK_{t+1} + (1-\delta)q_{t+1})\right] \tag{4.13}$$

∂N_t:

$$(1-\alpha)A\left(\frac{K_t}{N_t}\right)^{\alpha} = w_t \tag{4.14}$$

4.3.3 Aggregation

Since the cutoffs θ_t^* and θ_t^{**} do not depend on the realizations of $\theta_t(i)$ I can obtain economic aggregates that depend only on aggregate uncertainty. This is particularly desirable since there is no need to keep track of the distribution of state variables across location and allows to solve the model by linear approximation around a steady state with no aggregate uncertainty. Given a distribution $F(\theta)$ of the idiosyncratic shocks and letting $\upsilon_t = \frac{E\kappa_{t+1}}{\kappa}$, the aggregate variables κ_t, $\tilde{C}_t = \left(\int_0^1 \theta_t(i)c_t(i)^\rho di\right)^{\frac{1}{\rho}}$, $C_t = \int_0^1 c(i)_t di$, $S_t = \int_0^1 s(i)_t di$, $X_t = \int_0^1 x(i)_t di$ and $T_t = S_t + C_t - X_t$ are given as functions of θ_t^*,υ_t,η by

$$\phi_t \tilde{C}_t^{-\sigma} = \beta(1-d)E\kappa_{t+1}G(\theta_t^*, \upsilon_t, \eta)^{-\frac{1-\rho}{\rho}} \tag{E1}$$

$$\kappa_t = \phi_t \tilde{C}_t^{-\sigma} R(\theta_t^*, \upsilon_t, \eta) G(\theta_t^*, \upsilon_t, \eta)^{\frac{1-\rho}{\rho}} \tag{E2}$$

$$C_t = \tilde{C}_t D(\theta_t^*, \upsilon_t, \eta) G(\theta_t^*, \upsilon_t, \eta)^{-\frac{1}{\rho}} \tag{E3}$$

$$S_t = C_t \frac{H_1(\theta_t^*)}{D(\theta_t^*, \upsilon_t, \eta)} \tag{E4}$$

$$X_t = C_t \frac{H_2(\theta_t^*, \upsilon_t, \eta)}{D(\theta_t^*, \upsilon_t, \eta)} \tag{E5}$$

$$T_t = \frac{D(\theta_t^*, \upsilon_t, \eta) + H_1(\theta_t^*) - H_2(\theta_t^*, \upsilon_t, \eta)}{D(\theta_t^*, \upsilon_t, \eta)} C_t \tag{E6}$$

where $G(\theta^*, \upsilon, \eta)$, $D(\theta^*, \upsilon, \eta)$, $R(\theta^*, \upsilon, \eta)$, $H_1(\theta^*)$ and $H_2(\theta^*, \upsilon_t, \eta)$ are auxiliary functions that depend on the distribution chosen for θ. I define these auxiliary functions in Appendix E.

4.3.4 Equilibrium

The equations from the goods producing firm are already in terms of economic aggregates, to summarize them, we have

A labor demand equation

$$(1-\alpha)A_t K_t^{\alpha} N_t^{-\alpha} = a\frac{N_t^{\gamma}}{\kappa_t} \tag{E7}$$

An investment demand equation

$$\frac{I_t}{\bar{K}} - \delta = \frac{1}{\chi}(q_t - 1) \tag{E8}$$

The Euler equation for capital

$$q_t = E\left[\left(\frac{1}{1+r_{t+1}}\right)(MPK_{t+1} + (1-\delta)q_{t+1})\right] \tag{E9}$$

The capital law of motion

$$K_{t+1} = I_t + (1-\delta)K_t \tag{E10}$$

Finally, we have an Euler equation for savings

$$\kappa_t = \beta E(1+r_{t+1})\kappa_{t+1} \tag{E11}$$

and the aggregate resources constraint

$$C_t + S_t - (1-d)S_{t-1} + K_{t+1} - (1-\delta)K_t + \frac{\chi\bar{K}}{2}\left(\frac{I_t}{\bar{K}} - \delta\right)^2 + \eta X_t = A_t K_t^{\alpha} N_t^{1-\alpha} \tag{E12}$$

An equilibrium for the aggregated economy is given by sequences for the 12 endogenous variables

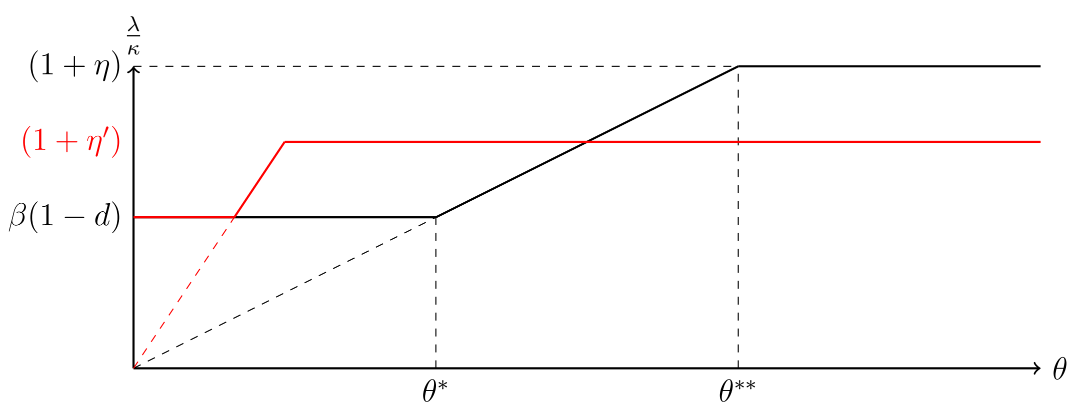
$$\left\{\kappa_t, q_t, r_t, \theta_t^*, \tilde{C}_t, C_t, S_t, X_t, T_t, K_{t+1}, I_t, N_t\right\}$$

that solve the dynamic system $E1$-$E12$, given initial values $\{K_0, S_0\}$, a process for the exogenous variable $\{\phi_t,\}$ and the distribution of the idiosyncratic shocks $F(\theta)$.

4.4 Solution and calibration

I derive a linear approximation of the model around a solution with $\phi_t = 1$. To compare the model after an improvement on distribution technology I use two calibrations such that the comparison model has a parameter $\eta' < \eta$. Figure 4.6 shows the effect of reducing η in the steady state solution of the model[3]. Improvement in distribution technology, reflected in $\eta' < \eta$, lowers the thresholds at which the household holds no inventories $s(i) = 0$ and starts ordering after the realization of $\theta(i)$, $x(i) > 0$.

Figure 4.6: The relative shadow values in steady state



For the calibrations of the model I assume a quarterly frequency and that the idiosyncratic shocks θ follow a Pareto distribution with shape parameter xi. For the benchmark calibration I assume that $\eta \to \infty$. I calibrate the elasticity of substitution ρ and ξ to match $1 - F(\theta^*) = 0.7$ and $\frac{S}{C} = 5$. I set the parameters of disutility of labor a and γ to match a fraction of hours worked of 0.2. The parameter for the adjustment costs of capital, χ is set to target a relative volatility of investment to

[3]For the solution to the steady state see appendix F.

GDP of 2.5. The rest of the parameters are chosen according to common values from the literature, shown in Table 4.1

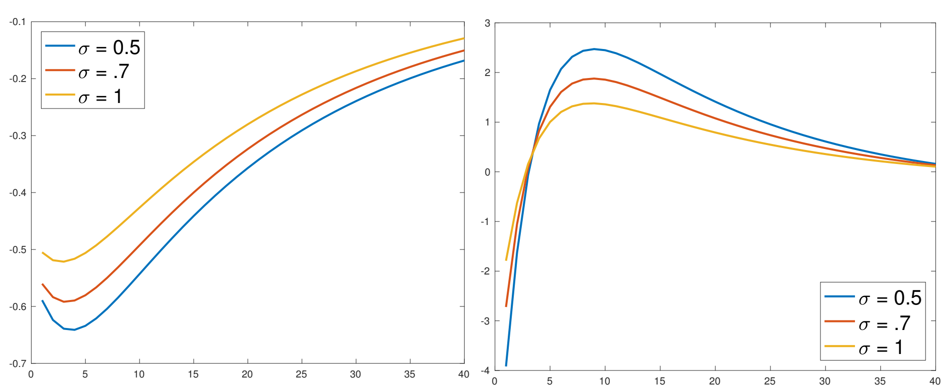
Table 4.1: Calibrated parameters

α	β	d	δ
0.3	0.99	0.015	0.025

Figure 4.7 shows the responses of the inventories to sales ratio and inventory investment to a shock to the aggregate demand shifter ϕ_t. The model generates a countercyclical ratio and a response of inventory investment that is procyclical at medium frequencies but countercyclical at high frequencies. This is consistent with the data on inventory investment. The volatility of both variables is higher for lower values of the intertemporal elasticity of substitution. Table 4.2 compares moments of the data with the model assuming an intertemporal elasticity of substitution of 0.5. The model does well except in two aspects. Consumption is more volatile than GDP in the calibrated model and the volatility of inventory investment and the inventory to sales ratio fall short when compared to the data.

Figure 4.7: Impulse-response to a demand shock

(a) Inventory to sales ratio (b) Inventory investment



The second calibration of the model has a value of η to match an inventory to sales ratio of 3, consistent with the fall in the data. Table 4.3 compares some variable moments between the benchmark calibration and the calibration with inventories to

Table 4.2: Model fit with a demand shock driven cycle

	Data		Model	
Variable	SD/Y	$corr./y$	SD/Y	$corr./y$
C	0.61	0.96	1.03	0.98
I	2.5	0.94	2.50	0.85
Is	22.1	0.43	8.76	0.24
S/C	0.83	-0.59	0.22	-0.83

sales ratio of $S/C = 3$. In the first two columns we can see that there is no important change in the cyclicality of either inventory investment or capital investment, both remain roughly as procyclical with the improvement in distribution technology. The last column shows that the correlation between inventory investment and capital investment falls with the improvement in distribution technology and it does so by an amount comparable to what we see in the data. The correlation in the second calibration is about a third of that in the benchmark, further, the relation goes from positive to practically null. We can conclude that the change in the relation between inventory and capital investment can in fact be explained by the same mechanism as the fall in the inventories to sales ratio: improvement in distribution technology. Given this result, I can now look at other effects of the improvement in distribution technology on aggregate investment.

Table 4.3: Relative changes in volatility of business cycle aggregates

Model	$corrI/Y$	$corrIs/Y$	$corrIs/I$
Benchmark	0.78	0.25	0.15
$S/C = 3$	0.83	0.16	0.06

Table 4.4 shows ratios of steady state values and volatilities of the second calibration divided by the benchmark[4]. As expected, we see in the first column that the second calibration has a substantially smaller stock of final goods, at 44% of the benchmark. This is explained by lower importance of inventories to deal with id-

[4]Values above 1 indicate a higher value in the second calibration. Values below one, higher values in the benchmark

iosyncratic uncertainty and can be seen reflected on the lower value of the parameter θ^*.

The second column shows a decrease in the volatility of capital investment of about 12% while the volatility of other economic aggregates remains relatively unchanged. This weakening volatility is one additional effect on aggregate capital investment from the change in its relation with inventory investment. This is explained by firms substituting future production with current production, done by increasing inventories and reducing capital investment. This result shows the importance of looking at inventory investment when studying the behavior of capital investment and opens up the question of what other valuable information on economic aggregates can be deduced from inventory data.

Table 4.4: Relative changes in volatility of business cycle aggregates

Variable	Steady State	Volatility
θ^*	0.81	0.99
Y	1	1.01
C	0.86	1.01
$\tilde{C}$	1.23	1.03
I	1	0.88
S	0.44	0.98

4.5 Conclusion

The behavior of final good inventories has changes in time starting in the 1980's. First, a reduction in the inventories to sales ratio that points towards improvement in distribution technology. Second, a weakening correlation between inventory and capital investment.

A theoretical framework in which inventories become less essential to produce sales can explain both empirical facts. As inventories are less important to produce sales, firms start holding them to smooth the cost of production. This causes inventory and capital investment to turn form complements in production of sales to substitutes. Through this mechanism, the volatility of aggregate capital investment after a demand shock falls, as part of the response that would normally come from capital is now taken by inventory investment. This result is promising in explaining at least partly the recent changes in capital investment, particularly the underinvestment puzzle.

APPENDIX A

Data

A.1 Aggregate data on shipments, new orders and unfilled orders

Aggregate and industry data on shipments, orders and unfilled orders comes from the publicly available historical series of the Census Bureau Manufacturers' Shipments, Inventories and Orders (M3) survey. The series have monthly frequency and are availble under SIC and NAICS classification for the periods: SIC: 1959m1-2001m3 and NAICS:1992m1-2018m12. I splice the SIC and NAICS series for the category of "Non-defense equipment and machinery excluding aircraft". I exclude aircraft from the analysis because this category has substantially higher unfilled orders and a much more countercyclical ratio than the rest. This way I make sure that my results are not driven by this category. To splice the series I apply growth rates from the SIC series to the first observation of the NAICS series and construct the series back. I deflate the series using the price index for Personal Consumption Expenditure Excluding Food and Energy before splicing. Figure (A.1) compares the resulting spliced series with the original SIC series. The period from 1992 to 2001 exists for both series and provides a test of how well the splicing works. For the three series, the spliced data lies above the SIC data, but for the overlap period they seem to follow the same behavior.

I aggregate the data to quarterly level. Shipments and new orders aggregate additively as flows, unfilled orders are a stock, I aggregate them by averages. To obtain cyclical components I run a Hodrick-Prescott filter on the natural logarithm of the series. The smoothing parameter is 1600. For the series of the ratio of unfilled orders to shipments, I take the HP-filter of the ratio in levels.

A.2 Firm level data from Compustat

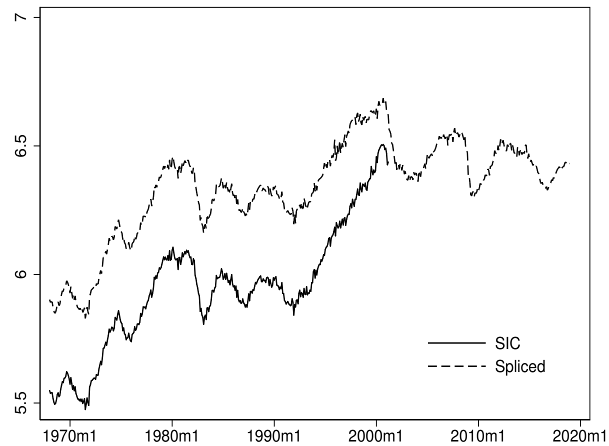
Compustat dataset comes mainly from the fundamentals annual dataset. I keep industrial reports ($indfmt == "INDL"$) in standard format ($datafmt == "STD"$) from firms consolidated ($consol == "C"$) in the U.S. ($fic == "USA"$) and reporting in dollars ($curcd == "USD"$). I keep the subset of manufacturing firms according to NAICS code 3.

To classify firms by type of capital they produce, I use the break-down from BEA NIPA Table 5.5.5. Private Fixed Investment in Equipment by Type. I matched these categories to NAICS codes using BEA's file "PEQBridge2007Detail.xls" which contains the bridge information to construct the mentioned table. I discuss the categories below when I describe the comprehensive tax subsidy.

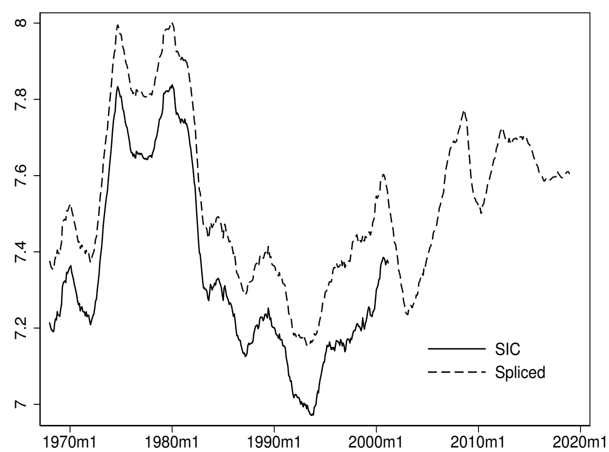
Variables in the dataset are GVKEY (Firm indicator), FYEAR (Year), year1 (first year the firm appears in a dataset), year2 (last year the firm appears in a dataset), OB (Order backlog), sale, invt (Total inventories), invfg (final good inventories), invwip (work in process inventories), xint (interest and related expenses), lt (total liabilitites), dlc (debt in current liabilities), dltt (long term debt), emp (employment) and oiadp (operating income after depreciation). The dataset spans the period from

Figure A.1: Spliced series for non-defense equipment escluding aircraft

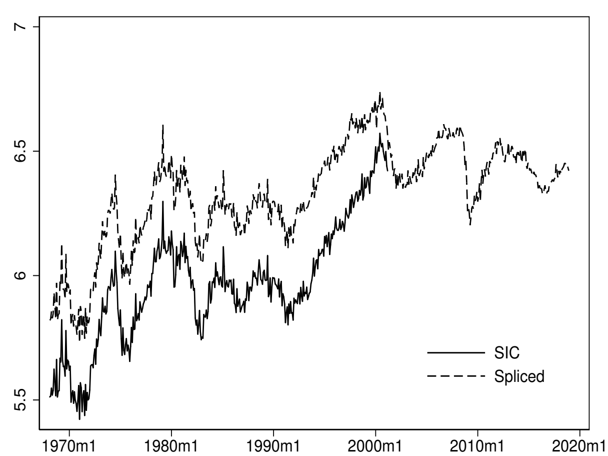
(a) Shipments



(b) Unfilled Orders



(c) New Orders



1974 to 2018.

I merge this dataset with the NBER CES productivity dataset and use its industry specific deflators to convert Compustat variables to constant dollars of 2011. The variables unfilled orders and shipments in my analysis correspond to ob and sale respectively. The unfilled orders to shipments ratio is the ratio of these two. I drop observations with missing values for shipments or unfilled orders and observations on the first and 99th percentile of the ratio of unfilled orders to shipments. I estimate the age of a firm by the difference between fyear and year1.

Controls: all empirical specifications have controls for: lagged $log(at)$, age, lagged $log(emp)$ and a Lerner index computed as

$$Lerner = \frac{oiadp}{sale}$$

.

The leverage ratio and financing costs are computed as

$$lev_t = \frac{dlc + dltt}{at}$$

$$r_t = \frac{xint}{lt}$$

I winsorize both variables at the first and 99th percentiles. Before using the financial variables to sort firms into quartiles, I demean them at the firm level. With this, the financial variables represent the deviation from the average position of the firm.

The compustat dataset is matched to the comprehensive tax subsidy using NAICS codes for the years between 1974 and 2009. I exclude the capital type “Aircraft” from my analysis for the reasons listed above.

A.3 Comprehensive tax subsidy

The data on the comprehensive tax subsidy was provided by Christopher House for the categories of type of equipment listed in NIPA NIPA Table 5.5.5. I match this to the Compustat dataset using NAICS codes. Categories by type of equipment are shown in Table (A.1).

Table A.1: Types of capital goods

1	Computers and peripheral equipment
2	Communication equipment
3	Electro-medical equipment
4	Medical instruments
5	Nonmedical instruments
6	Photocopy and related equipment
7	Office and accounting equipment
8	Fabricated metal products
9	Engines and turbines
10	Metalworking machinery
11	Special industry machinery, not elsewhere classified
12	General industrial, including materials handling, equipment
13	Electrical transmission, distribution, and industrial apparatus
14	Trucks, buses, and truck trailers
15	Autos
16	Ships and boats
17	Railroad equipment
18	Furniture and fixtures
19	Agricultural machinery
20	Construction machinery
21	Mining and oilfield machinery
22	Service industry machinery
23	Electrical equipment, not elsewhere classified

APPENDIX B

Notes on the partial equilibrium models

B.1 Proof of Proposition 1

Proof. I can write the delivery lag as $\frac{UFO_t}{Ship_t} - 1$. As $\frac{UFO_t}{Ship_t}$ increases, the constraint $UFO_t \geq Ship_t$ gets farther from binding. Now, I can express the shadow price μ as

$$\mu_t = \sum_{s=0}^{\infty} E[\beta^s \pi_{t+s}]$$

This is, the shadow price of an unfilled order is the discounted sum of the expected values of the constraint binding. As $\frac{UFO_t}{Ship_t}$ increases, the constraint slacks more, bringing the expected values of it binding in the future and the shadow price μ down. $\square$

B.2 Proof of Proposition 2

Proof. Under convex new orders, the policy function $Ship(UFO, P)$ approaches the convexity of new orders when close to the constraint. From Corollary 1 $Ship(UFO, P)$ approaches the concave function $S(P)$ as it pulls away from the constraint. Then, it must be that $Ship(UFOP)$ is less concave in prices than $S(P)$ which implies that

$$C(Ship(P))Ship(P) > 1$$

$\square$

APPENDIX C

Robustness of the empirical results

C.1 Investment Tax Credit

I show in Table (C.1) the estimated change in the unfilled orders to shipments ratio after a 1% increase in the comprehensive tax subsidy (column 1) and the Investment Tax Credit (column 2). The conclusions from Section 2.5 carry over when using the ITC. Constraint firms respond to the tax incentives by actually increasing their unfilled orders to shipments ratio while their unconstrained counterparts in all other quartiles, reduce it.

C.2 Shadow of death

I show in Table (C.2) the specification using the leverage-ratio to sort firms into quartiles. For this specification I exclude firm-year observations that correspond to the last year a firm shows in the dataset. The order and conclusions from Section 2.5 carry over although the estimated coefficients are smaller and loose some statistical significance.

Table C.1: Estimated responses to a 1% change in tax incentives

	ζ	ITC
TC	-0.050	0.017
	(0.037)	(0.112)
Q^3TC	-0.014	-0.052
	(0.010)	(0.016)
Q^2TC	-0.029	-0.063
	(0.001)	(0.017)
Q^1TC	-0.022	-0.039
	(0.006)	(0.017)
N	4283	4283

Table C.2: Estimated responses to a 1% change in tax incentives

	$log(Ship)$	$log(UFO)$
ζ	2.198	2.689
	(1.662)	(1.955)
$Q^3\zeta$	0.374	-0.0948
	(0.230)	(0.433)
$Q^2\zeta$	0.285	-0.607
	(0.281)	(0.419)
$Q^1\zeta$	0.393	-0.162
	(0.134)	(0.0706)
N	4184	4184

APPENDIX D

Notes on the general equilibrium model

D.1 Equilibrium definition

An equilibrium in this economy, given the process for the productivity shock $\varphi_t(\varphi_{t-1}, \varepsilon_t)$ is given by

transition functions for

1. Aggregate state

$$\Psi_t = \{UFO(\Psi_{t-1}, \varphi_t), K(\Psi_{t-1}, \varphi_t)\}$$

2. Household state variables

$$\psi_t^{hh} = \left\{ufo(\psi_{t-1}^{hh}, \Psi_{t-1}, \varphi_t)\right\}$$

3. Capital producer state variables

$$\psi_t^{kp} = \left\{ufo^{kp}(\psi_{t-1}^{kp}, \Psi_{t-1}, \varphi_t), X(\psi_{t-1}^{kp}, \Psi_{t-1}, \varphi_t)\right\}$$

policy functions for

1. Aggregate

$$\mathcal{Y}_t = \{NO(\Psi_{t-1}, \varphi_t), Ship(\Psi_{t-1}, \varphi_t)\}$$

2. Household

$$\begin{aligned} y_t^{HH} = &\big\{C(\psi_{t-1}^{HH}, \Psi_{t-1}, \varphi_t), N(\psi_{t-1}^{HH}, \Psi_{t-1}, \varphi_t), \\ &B(\psi_{t-1}^{HH}, \Psi_{t-1}, \varphi_t), no^{hh}(\psi_{t-1}^{HH}, \Psi_{t-1}, \varphi_t)\big\} \end{aligned}$$

3. Capital goods producer

$$y_t^{kp} = \Big\{I(\psi_{t-1}^{kp}, \Psi_{t-1}, \varphi_t), WC(\psi_{t-1}^{kp}, \Psi_{t-1}, \varphi_t), D(\psi_{t-1}^{kp}, \Psi_{t-1}, \varphi_t)\Big\}$$

and **prices**

$$\big\{P(\Psi_{t-1}, \varphi_t), \bar{P}(\Psi_{t-1}, \varphi_t), r(\Psi_{t-1}, \varphi_t)\big\}$$

such that

1. $NO_t = no_t^{hh} = no_t^{kp}$, $UFO_t = ufo_t^{hh} = ufo_t^{kp}$, $Ship_t = \ell_t UFO_t = \theta X_t$ and $B_t = 0$
2. Households maximize utility given states according to (2.26)
3. Capital goods producers maximize profits given states according to (**??**)
4. Households budget constraint (2.25) and laws of motion (2.24), (2.23) are satisfied
5. Producers laws of motion (2.20) and (**??**) are satisfied
6. The aggregate resources constraint (2.27) and law of motion for aggregate unfilled orders (2.13) are satisfied

D.2 First order conditions

1. Law of motion UFO

$$UFO_t = UFO_{t-1} - \theta X_{t-1} + NO_t \tag{D.1}$$

2. Law of motion aggregate capital

$$K_{t+1} = (1-\delta)K_t + \theta X_t \tag{D.2}$$

3. Law of motion Work-in-process

$$X_t = (1-\theta)X_{t-1} + fracI^{\gamma}b\gamma \tag{D.3}$$

4. Labor supply

$$\psi N_t^{\frac{1}{\eta}} = \frac{F_2(K_t, N_t)}{C_t} \tag{D.4}$$

5. Euler equation capital

$$q_t = \beta E\left[C_{t+1}^{-1}F_1(K_{t+1}, N_{t+!}) + (1-\delta)q_{t+1}\right] \tag{D.5}$$

6. Euler equation bonds

$$C_t^{-1} = (1+r_t)\beta E\left[C_{t+1}^{-1}\right] \tag{D.6}$$

7. Euler equation UFO producer

$$\pi_{1t} = \mu_t - \beta E\left[\frac{C_{t+1}^{-1}}{C_t^{-1}}\mu_{t+1}\right] + R_1(UFO_t, D_t) \tag{D.7}$$

8. Euler equation UFO household

$$M_t = \ell_t(q_t - (1-\kappa_1)C_t^{-1}\bar{P}_t + (1-\ell_t)\beta E[M_{t+1}] \tag{D.8}$$

9. Euler equation Work in process

$$(1-\kappa_{1t})\theta\bar{P}_t - \beta E\left[\theta\frac{C_{t+1}^{-1}}{C_t^{-1}}\mu_{t+1}\right] = \pi_{1t} + \lambda_t - \beta E\left[\theta\frac{C_{t+1}^{-1}}{C_t^{-1}}\lambda_{t+1}\right] \tag{D.9}$$

10. Work-in-process demand

$$\lambda_t = (1+\kappa_2\pi_{2t})bI_t^{1-\gamma} \tag{D.10}$$

11. Orders supply

$$\mu_t = \xi - \kappa_1 P_t(1+\pi_{2t}) \tag{D.11}$$

12. Orders demand

$$M_t = \kappa_1 P_t C_t^{-1} \tag{D.12}$$

13. Orders constraint

$$(UFO_t - X_t)\pi_{1t} = 0 \tag{D.13}$$

14. Aggregate resources constraint

$$C_t + I_t + \xi NO_t = F(K_t, N_t) \tag{D.14}$$

15. Productivity process

$$Log(\varphi_t) = \rho log(varphi_{t-1}) + \varepsilon_t \tag{D.15}$$

16. Price process

$$\bar{P}_t UFO_t = \bar{P}_{t-1}(UFO_{t-1} - \theta X_{t-1}) + P_t NO_t \tag{D.16}$$

17. Working capital constraint

$$WC_t - \kappa_2 I_t)\pi_{2t} = 0 \tag{D.17}$$

18. Debt constraint

$$\pi_{3t} D_t = 0; \tag{D.18}$$

19. Debt demand

$$\pi_{3t} + \pi_{2t} = R(UFO_t, D_t) + R_2(UFO_t, D_t) \tag{D.19}$$

APPENDIX E

Auxiliary functions of the distribution of θ

$$f_1(\theta^*) = \int\limits_{\theta<\theta^*} \theta^{\frac{1}{1-\rho}} dF(\theta)$$

$$f_2(\theta^*, \eta, \upsilon) = \int\limits_{\theta^*}^{\theta^{**}} \theta dF(\theta)$$

$$f_3(\theta^*, \eta, \upsilon) = \int\limits_{\theta^{**}}^{\infty} \theta^{\frac{1}{1-\rho}} dF(\theta)$$

With $\upsilon_t = \frac{E\kappa_{t+1}}{\kappa}$ and so $\theta^{**} = \frac{1+\eta}{\beta(1-d)} \frac{\theta_t^*}{\upsilon^t}$. All economic aggregates can now be written in terms of the functions

$$G(\theta^*, \upsilon, \eta) = f_1(\theta^*) + (\theta^*)^{\frac{\rho}{1-\rho}} f_2(\theta^*, \eta, \upsilon) + \left(\frac{\beta(1-d)}{(1+\eta)} \upsilon_t \right)^{\frac{\rho}{1-\rho}} f_3(\theta^*, \eta, \upsilon)$$

$$D(\theta^*, \upsilon, \eta) = f_1(\theta^*) + (\theta^*)^{\frac{1}{1-\rho}} \left[F(\theta^{**}) - F(\theta^*) \right] + \left(\frac{\beta(1-d)}{(1+\eta)} \upsilon_t \right)^{\frac{1}{1-\rho}} f_3(\theta^*, \eta, \upsilon)$$

$$R(\theta^*, \upsilon, \eta) = F(\theta^*) + \frac{1}{\theta^*} f_2(\theta^*, \eta, \upsilon) + \frac{1+\eta}{\beta(1-d)} \frac{1}{\upsilon_t} (1 - F(\theta^{**}))$$

$$H_1(\theta^*) = (\theta^*)^{\frac{1}{1-\rho}} F(\theta^*) - f_1(\theta^*)$$

$$H_2(\theta^*, \upsilon_t, \eta_t) = \left(\frac{\beta(1-d)}{1+\eta} \upsilon_t \right)^{\frac{1}{1-\rho}} f_3(\theta^*, \eta, \upsilon) - (\theta^*)^{\frac{1}{1-\rho}} [1 - F(\theta^*)]$$

APPENDIX F

Model steady state

In steady state $\upsilon = 1$ and with determined values for ϕ, A and η, all of the auxiliary functions $G, R, D, H1$ and $H2$ are just functions of the steady state value of θ^*. From E9 we have $r = \frac{1-\beta}{\beta}$. The value of θ^* is determined by an equation that results from combining E1 and E2

$$R(\theta^*) = \frac{1}{\beta(1-d)}$$

from E8

$$\frac{K}{N} = \left(\frac{\alpha A}{r+\delta}\right)^{\frac{1}{1-\alpha}}$$

and given a steady state value of $N = 1/3$ this determines K as well. From equation E10 consumption is determined

$$C = \left(1 + d\frac{H1}{D} + \eta\frac{H2}{D}\right)^{-1} \left(AK^{\alpha}N^{1-\alpha} - \delta K\right)$$

equations E3 and E4 determine $\tilde{C}$ and κ respectively

$$\tilde{C} = \frac{G^{\frac{1}{\rho}}}{D}C$$

$$\kappa = \phi \tilde{C}^{-\sigma} R G^{\frac{1-\rho}{\rho}}$$

Finally, S, X and T are determined as functions of C by equations E4, E5 and E6 respectively. The residual equation E7 yields a value for parameter a, consistent with the desired steady state level of labor.

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