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UNCOVERING THE INVENTORY-BUSINESS CYCLE NEXUS

by Luca Rossi*

Abstract

Despite being the smallest component of GDP, inventories represent the second largest source of GDP fluctuations, with a contribution comparable to that of fixed investment. Over the past decades, research in inventory management has proposed competing theories about the primary drivers prompting firms to accumulate stocks, yet consensus remains elusive on the source of inventory cycles. This paper imposes structure on US macroeconomic data and disentangles four shocks related to current and expected demand and supply conditions within a unified framework. We find that sales forecast errors drive the highest share of inventory investment in the short run, giving support to the buffer-stock motive for holding inventories, whereas shocks to expected costs gain more relevance in the long run and generate the missing positive correlation between cost-driven inventory investment and sales that the literature has struggled to find. Shocks to expected demand – which relate to stockout-avoidance reasons for inventory investment – are also very relevant. We find that forward-looking behaviours are those that lead production to be more variable than sales. Finally, our results offer a sensible narrative around the post-pandemic period when inventories drove a very high share of GDP fluctuations.

JEL Classification: C32, C50, E22, E32.

Keywords: inventory investment, Bayesian Vector Autoregressive Models, sign restrictions.

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* Bank of Italy, Directorate General for Economics, Statistics and Research. E-mail: luca.rossi@bancaditalia.it

"*Inventory fluctuations are important in business cycles; indeed, to a great extent, business cycles are inventory fluctuations*", Blinder (1981).

Introduction[1]

Understanding the business cycle is a central task for applied macroeconomists and forecasters, and the resulting analyses have repercussions on decisions taken by policymakers, firms, and the financial sector. In the US, household consumption usually attracts the highest attention: with Personal Consumption Expenditures (PCE) making up almost 70% of GDP as of 2023, even relatively small movements in households' consumption can generate large variations in GDP figures. On the other side of the spectrum, inventory investment is by far the smallest component of the expenditure side of GDP, usually counting as little as less than one percent of GDP in absolute value. Nevertheless, despite its very small size inventory investment gives a large contribution to overall economic growth (see Figure 1). Since 1990, inventory investment turns out to be on average the second largest contributor to quarterly GDP growth together with fixed investment, with both categories being responsible for an average absolute contribution equal to 1.1 percentage points at every quarter. Expanding the sample to 1947 - its starting date - inventory investment is even more relevant. This stylized fact is well known and was first documented by Abramovitz (1950) and later Blinder (1980); the latter paper finds that inventory disinvestments accounted for 70% of GDP contractions in the average post-war recessions. Table 1 updates the same accounting and - if we exclude the two recessions that began in the 1960s where GDP contracted less than $10 billion, making the exercise uninteresting in those instances - the updated share on the longer sample is on average equal to 50.6%, still a sizeable number.[2]

Knowing the sources of inventory fluctuations is important not only for business cycle analysis but also for forecasting economic activity. In the US, in the days surrounding the publication of the advance (i.e. the first) estimate of GDP growth, two months of PCE data as well as retail sales for the third month of the relevant quarter are already available. This means that a large share of surprises in GDP releases are driven by the

[1] I thank Luisa Carpinelli, Riccardo Cristadoro, Filippo Natoli, Sergio Santoro, Massimiliano Sfregola and Luigi Federico Signorini for valuable comments and suggestions. The views expressed in this paper are those of the author and do not necessarily reflect those of the Bank of Italy. All remaining errors are mine.

[2] Interestingly, Blinder (1981) highlights the puzzle that in the 1980 recession inventory investment increased, and attempts at giving explanations for this apparent contradiction. Our table show that this was probably due to measurement error, as newest figures show that even then inventory investment was negative.

remaining components for which data are available only with additional lags or with a lower frequency. Given its high volatility, inventory investment therefore drives a lot of GDP growth forecast errors.[3]

A fundamental issue that has hindered a consistent rationalization of inventory investment is that its contribution to GDP growth is very erratic and hardly predictable. Garciga and Knotek II (2019) for instance provide evidence of a notable increase in GDP growth forecasting performance when one subtracts inventories from the autoregressive component of GDP; Morley and Singh (2016) find that smaller transitory inventory shocks during the Great Moderation lie at the root of the relatively higher reduction of GDP volatility as compared to that of sales during that period.[4] Part of the lack of understanding of inventory dynamics is that - as it is well known at least since Lundberg (1937) - inventory investment can sometimes decrease because of good news about the economy: higher-than-expected demand pushes firms with production lags to draw down their investment stocks, and vice versa when demand is unexpectedly low. This thus means that while buoyant aggregate demand is reflected in higher consumption, firms will in this case be constrained to disinvest in inventories, creating a countervailing force on GDP that can be as high as the size of the unexpected increase in consumption.[5] Those news are one of a few fundamental shocks that hit inventories, and without a model that recovers all of them it is hard to have a complete understanding of what drives the broad macroeconomy to accumulate stocks.

Importantly - and as somewhat acknowledged in Blinder (1986b) - many of the empirical strategies previously employed by the literature to study the drivers of inventory investment cannot easily be given a structural interpretation as the regressions proposed are plagued by contemporaneous causality and omitted variables. In their discussion on inventories, Ramey and West (1999) acknowledge that the literature did not attempt to extract the source of shocks, but that inventories data may indeed be used also to accomplish this goal.[6] Their review concludes that the existing evidence does not allow to have a definitive answer on which of cost versus demand shocks matter more, and advocate more research on the topic. Absent a systematic analysis or representative surveys,

[3]Using data from Refinitiv starting in 2009, the correlation between consensus forecast errors in the advance estimate of GDP growth and the contribution of inventory investment to GDP growth is equal to 43.2%, and the relationship after 2020 is substantially stronger.

[4]In this paper, as in the rest of the literature, sales are defined as GDP net of inventory investment.

[5]The above countercyclical movement does not occur when firms correctly anticipate the rise in demand with sufficient advance, as they will prepare and replenish their warehouses with the stocks they need, something that adds momentum to a coming economic boom.

[6]From Ramey and West (1999): "*While in principle it may be possible to pin down important macroeconomic parameters and sources of shocks by simply estimating linear inventory models with aggregate data, this tantalizing idea has not proved true in practice so far*".

joint evidence on the importance of different demand or supply channels in driving this important component of GDP is as of today mostly anecdotal.

To the best of our knowledge, we are the first to address the above issue within a unified empirical framework, jointly identifying supply and demand shocks for current and future conditions through a Structural VAR with sign restrictions.[7] Our approach encompasses in a consistent way the effects stemming from buffer stock motives, cost shocks, and stockout avoidance mechanisms that lead firms to invest or disinvest in inventories. We do this by imposing structure on aggregate data - inventory investment, goods prices, production, and firms' assessment of future business activity - and disentangle the determinants of inventory investment in the US, thus providing a useful toolbox to better understand an important piece of the business cycle.

The identified shocks can be related to some of the most relevant theories that have been put forward to explain why firms invest in inventories, and the resulting variance decomposition thus suggests which theory best explains the data. First, our current demand shock induces disinvestment in inventories and leads firms to increase production so as to replenish their stocks, as in Lovell (1961). Second, a shock to expected demand raises production in order to raise stocks in anticipation of future demand, which is the stockout-avoidance motive modeled in Kahn (1987) who explains part of the puzzle that production is more variable than sales. Third, negative shocks to expected supply push firms to accumulate precautionary stocks in order to exploit lower current costs, as suggested in Mack (1953) and formalized in Blinder (1986a). Fourth and final, we also add a current supply shock which is important to explain periods such as those characterized by supply-chain bottlenecks after the pandemic, where firms found themselves suddenly unable to expand production and inventories as desired.

For very short horizons we find that shocks to current demand drive the highest share of variance among the shocks we consider, which supports the view that at an aggregate level inventories indeed usefully serve as a buffer to absorb unexpected fluctuations in demand. This is an important result as the literature has struggled to provide empirical evidence in favor of this hypothesis, and we thus argue that the unpredictability of inventory investment at very high frequencies is mainly driven by inherently unpredictable sales forecast errors.[8] We corroborate this by showing the existence of a strong correla-

[7] Within a general equilibrium framework, Wen (2011) and Auernheimer and Trupkin (2014) introduce demand and supply shocks, without nevertheless attempting to answer the question of which of them is empirically more relevant.

[8] See for example the discussion in Blinder and Maccini (1991). Wen (2005) finds reduced-form evidence that points in this direction, showing that the bulk of variation in inventory investment stems from higher-frequency, countercyclical movements.

tion between professional forecasters' retail sales forecast errors and our current demand shocks. Over longer horizons, the forward-looking nature of inventory investments takes center stage: shocks to future costs are responsible for almost a third of the variation in inventory investment, lending support to Blinder (1986a) and Eichenbaum (1989). Our results also clearly highlight that expected cost shocks generate a positive correlation between inventory investment and sales that the literature struggled to find and that allows to rationalize the fact that output is more variable than sales. In accordance with Kahn (1992), stockout-avoidance reasons also explain a large amount of variation in the data and we show that together with expected supply shocks they also empirically explain why production is more variable than sales.

Our model proves useful also to understand single episodes where inventories generated substantial business cycle fluctuations as happened after 2020, in particular i) the gyrations of demand and supply expectations in the immediate aftermath of the pandemic; ii) supply chain bottlenecks; iii) bullwhip effects; iv) the real effects of the 2021 fiscal stimulus; v) the war in Ukraine.

Finally, we map our monthly results onto quarterly contributions of inventory investment to GDP growth. We deem this to be of great interest since as we said there are instances where e.g. unexpected good news are a drag on GDP growth because firms decumulate stocks to accommodate strong demand, something that does not happen when the increase in demand is expected as firms build up stocks pre-emptively. Thus, lower-than-expected GDP growth could be caused by good news and confound business cycle analysts about the current and future direction of the economy. In Section 4.4 we provide a case study that shows this issue in practice.

Admittedly, our model does not attempt to answer the question of why firms hold inventories to begin with and which general equilibrium effects their holding generate - a question that has shaped much of the literature on inventories - but rather explains why firms invest or disinvest in inventories at a given point in time, which is ultimately what business cycle analysts are interested to. As Wang et al. (2014) remark, after many years of research the inherent very high volatility of inventory investment still remains a mystery yet to be explained.

1 Related literature

The literature on inventory dates back many decades ago. Metzler (1941) extends a framework introduced in Lundberg (1937) by assuming that firms manage stocks actively rather than passively, responding to unexpected sales dynamics by adjusting inventories

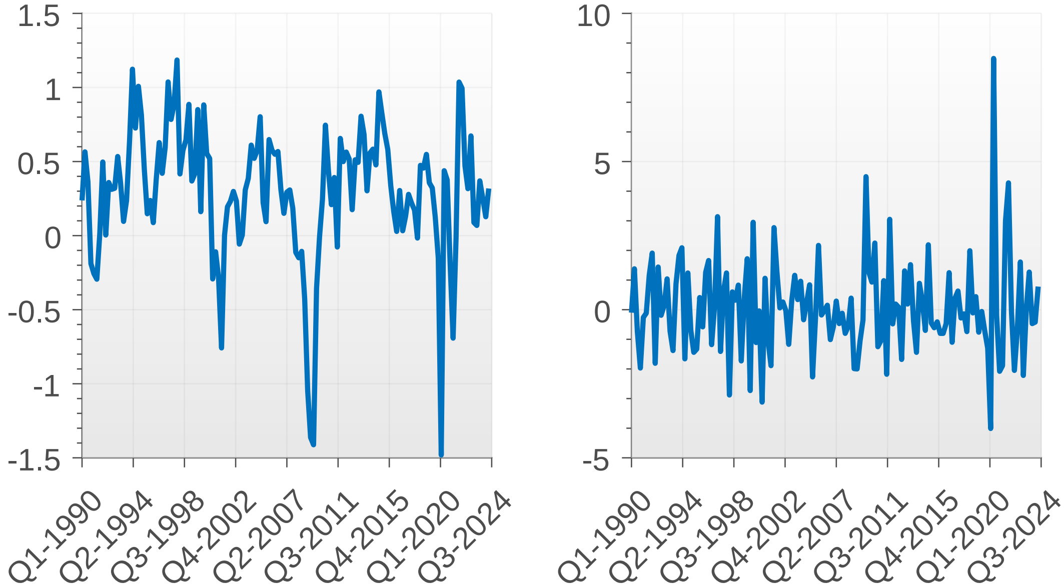

Figure 1: Change in private inventories. The left panel shows nominal change in inventories as a share of nominal GDP. The right panel plots the contribution of change in inventories to annualized real GDP growth.

Table 1: Changes in GDP and in inventory investment in recessions

Period	Change in GDP	Change in inventory investment	Change in inventory investment as a percentage of change in GDP
1948:4-1949:4	-35.0	-46.1	131.6
1953:2-1954:2	-70.9	-27.7	39.1
1957:3-1958:2	-96.2	-24	25.0
1960:2-1961:1	-4.5	-24.2	533.3
1969:4-1970:4	-8.9	-40.6	457.1
1973:4-1975:1	-193.1	-90.7	47.0
1980:1-1980:3	-159.8	-76.2	47.7
1981:3-1982:4	-188.6	-136.5	72.4
1990:3-1991:1	-138.7	-53.1	38.3
2001:1-2001:4	70.5	-70.0	
2007:4-2009:2	-646.0	-250.4	38.8
2019:4-2020:2	-1916.3	-302.9	15.8

Periods correspond to NBER recession dates. Figures are expressed in chained prices. GDP rose during the 2001:1-2001:4 recession, so we do not calculate change in inventory investment as a percentage of change in GDP in this case.

accordingly, targeting a given "normal" level or an inventory-sales ratio. Metzler (1941) shows that for business cycles to be generated it is sufficient to have firms attempting to recover unexpected inventory losses, giving rise to what he calls pure inventory cycles. Moreover, he finds that firms attempting to stabilize inventories around a target level can lead the larger economy to be destabilized, as unexpected demand lowers inventories, and firms add to demand by placing new orders to refill stocks. Lovell (1961) formalizes the so-called production smoothing-buffer stock model, where the author assumes increasing marginal costs of production, which make it optimal for firms to smooth production relative to sales, thereby accumulating and decumulating inventories even in the hypothetical case of variable but deterministic sales. The model also allows for the fact that demand has an unpredictable component, so firms hold inventories also to be prepared in case demand turns out to be unexpectedly high. Blinder (1981) notes a number of issues with the above model. First, empirical estimates suggest that the buffer stock motive is unimportant, and that the estimated speed of adjustment of inventories towards the desired level is unplausibly slow. Second, he argues that the assumption of increasing marginal costs is not realistic for retailers who more likely will face constant or decreasing marginal costs because of quantity discounts. Finally, and most importantly, the theory cannot explain the stylized fact that production is more variable than sales, as in fact it predicts the opposite is true. Blinder (1986a) proposes a way to save the production smoothing-buffer stock model: if firms face cost shocks in addition to demand shocks, and if they observe them before they decide the level of production and inventories, then under sufficiently large cost shocks production can become more variable than sales as firms anticipate production to earlier periods when costs are still low. Following Arrow et al. (1951), Blinder (1981) proposes a (S, s) model, where he assumes that retailers face a fixed cost of receiving products from manufacturers, and marginal costs are constant. This makes optimal for firms to let inventories fall until a minimum s level is reached, and then refill their warehouses up to the desired level S, thereby minimizing the number of transactions. This model is argued to be a better alternative for retail inventories to the production-smoothing model, which was rather developed for manufacturers' inventories whose dynamics are generated by quite different motives.

By imposing nonnegativity constraint to a stockout-avoidance model, Kahn (1987) accounts for the fact that production is more volatile than sales. In particular, he argues that when demand is serially correlated, a positive shock to demand reduces inventories but also increases expected demand. The first effect would render production as variable as sales, whereas the second suffices to make production more variable than sales. Moreover, the possibility to backlog excess demand allows the firm to smooth sales, whereas production still responds to previous period's demand. This alone is also sufficient to have production to be more variable than sales. Kahn (1987) then concludes that the existence of production counter-smoothing is not necessarily related to which of cost shocks versus demand shocks matter the most. Blinder and Maccini (1991) question the validity of the production smoothing-buffer stock model of inventories. Among the criticisms, the authors argue that sales and inventory investment are positively, not negatively, correlated, raising concerns about the fact that inventories serve as a buffer. They then argue that one should look at the relationship between unanticipated sales and unanticipated inventory investment, recalling that previous studies found small correlations. Christiano (1988) acknowledges that fixed investment and consumption do not respond immediately to disturbances within a given quarter. Thus, inventory investment is the category that moves the most against unexpected shocks, acting like a residual that balances demand and output. As Christiano (1988) himself puts it: "*In their role as a residual, inventories buffer consumption from unexpected disturbances in production and buffer production from unexpected disturbances in consumption*". While he quantifies that this property accounts for more than half of inventory investment volatility, his model cannot disentangle which of supply or demand matters the most. Kahn and Thomas (2007) provide the first microfounded general equilibrium model that can replicate the most important stylized facts about inventory dynamics. The authors find that if inventories were to disappear, GDP would not be less volatile, the reason being that in general equilibrium there is a trade-off between investment in inventory against consumption and capital investment. Smaller fluctuations in inventory investment are accompanied by greater fluctuations in the sum of the other two categories. Within a general equilibrium framework, Wen (2011) finds that inventory investment stabilizes rather than destabilize the economy. The reason is that, while procyclical inventory investment raises the volatility of production given sales, the volatility of sales is nevertheless reduced thanks to a procyclical return to inventory investment induced by a procyclical probability of stockout; this raises the price of final goods and thus reduces sales.

Görtz et al. (2022) provide evidence that positive shocks to future Total Factor Productivity (TFP) lead to a rise in inventories; this is not in contrast with our paper since the authors focus on non-stationary technology news shocks, whereas we look at transitory, short-term fluctuations in production costs.[9] In this respect, our setting is closer to Crouzet and Oh (2016) who assume that temporary declines in expected productivity spur firms to accumulate inventories in anticipation of higher future costs.

[9] Görtz et al. (2024) later find that the response of inventory investment to future TFP shocks is driven by reduced real rates of return rather than by changes in marginal costs.

Finally, the use of inventories and sign-restricted VARs to identify demand and supply shocks related to current and future economic conditions was first introduced by Kilian and Murphy (2014) who separate the speculative demand of oil from its more fundamental drivers. Gazzani et al. (2024) estimate a daily VAR and employ a different identification strategy to also extract current and forward-looking demand as well as supply components of oil prices, in real time. Our application is entirely different from theirs. Moreover, we leverage additional information on agents' expectations of future business activity to disentangle also shocks to expected supply arising e.g. from anticipated supply chain bottlenecks hitting the economy, a phenomenon that has proved to be able to generate economic cycles on its own and whose origins therefore deserve to be traced back separately from other shocks.

2 Data

We rely on a monthly Bayesian VAR with sign restrictions and uninformative priors (Arias et al., 2018) that disentangles structural shocks - which we describe in the next section - from the series of change in real nonfarm inventories available from the Bureau of Economic Analysis (BEA). We prefer to use nonfarm inventories rather than manufacturing and trade inventories as the former are a more comprehensive measure of stocks.[10] Monthly inventories figures are published approximately two months after their realization. This means that in the days surrounding the first GDP release our model is able to explain inventory investments for the first two months of the quarter, while one has to wait a few more weeks to have the full quarterly picture. In order to control for the expanding size of the US economy, we normalize inventory investment by the monthly real GDP series published by S&P Global.

Other than the absolute change in real nonfarm inventories, we feed the BVAR with the logarithm of the goods PCE deflator, the logarithm of Industrial Production, and the Philadelphia Fed Future General Business Activity index. All series are seasonally adjusted. As we show below, those variables prove very useful to discipline the model which thus exploits information on quantity, prices, and expectations. The model is run for the period January 1997 - June 2024 using six lags.

Before delving into the model specifics, we dedicate the remainder of this section to discuss two issues: the first is related to the quality of US inventory data, while the other

[10] Manufacturing and trade inventories make up between 86.5% and 90.0% of nonfarm inventories within our sample. Section 4.5 shows that our results are very robust to using the slightly less complete definition of inventories. Business cycle analysts might nevertheless prefer to use manufacturing and trade inventories as they are released before nonfarm inventories.

Table 2: Correlations between revisions in change in private inventories and components of GDP

	From 1^{st} to 2^{nd} estimate	From 2^{nd} to 3^{rd} estimate	From 1^{st} to final estimate
Consumption	-0.17	0.22	0.13
Fixed investment	0.01	0.16	0.08
Public expenditure	0.17	0.26	0.06
Exports	0.16	0.01	-0.03
Imports	0.04	-0.14	-0.05
Net exports	0.06	0.17	0.06

The table reports the correlations between different rounds of revisions in subcomponents of GDP with change in private inventories. Estimates are based on quarterly data expressed in constant prices.

makes the case for using monthly - as opposed to quarterly - data in settings like ours.

In a recent paper, Asimakopoulos et al. (2024) show that various euro area national statistical agencies tend to be reluctant in revising aggregate GDP estimates, while they are much more willing to update its subcomponents. In particular, they provide evidence that inventory investment revisions tend to offset those in other expenditure-side components of GDP, suggesting that the adjustment in inventories might be intended to mitigate changes in subsequent GDP releases. Below we perform a similar exercise by estimating the correlation between different rounds of revisions in all subcomponents of US GDP. In this way we can check to what extent the BEA adopts similar strategies as its European counterparts, namely, whether it significantly adjusts inventory data to make up for the differences between the production- and demand-side estimates of GDP. Table 2 reveals that this does not seem to be the case, as correlations are very small in absolute value and only four out of eighteen are negative.

Based on this analysis, it therefore seems reasonable to use available US inventory data as reliable estimates of firms' actual stock accumulation - it has indeed been commonly done by the rest of the inventory literature studying the US. In addition - had those data been chiefly driven by noise - we would likely not have found the results and narrative shown below.

Finally, we argue that our model cannot credibly be estimated for countries that only report inventory data at quarterly frequencies - most notably euro area Member States. Figure 2 plots the share of delivery lead times that are lower than 90 days for Maintenance, Repair and Operations (MRO) supplies and production materials in the US. In other words, it gauges the extent to which firms are able to adjust their stocks within

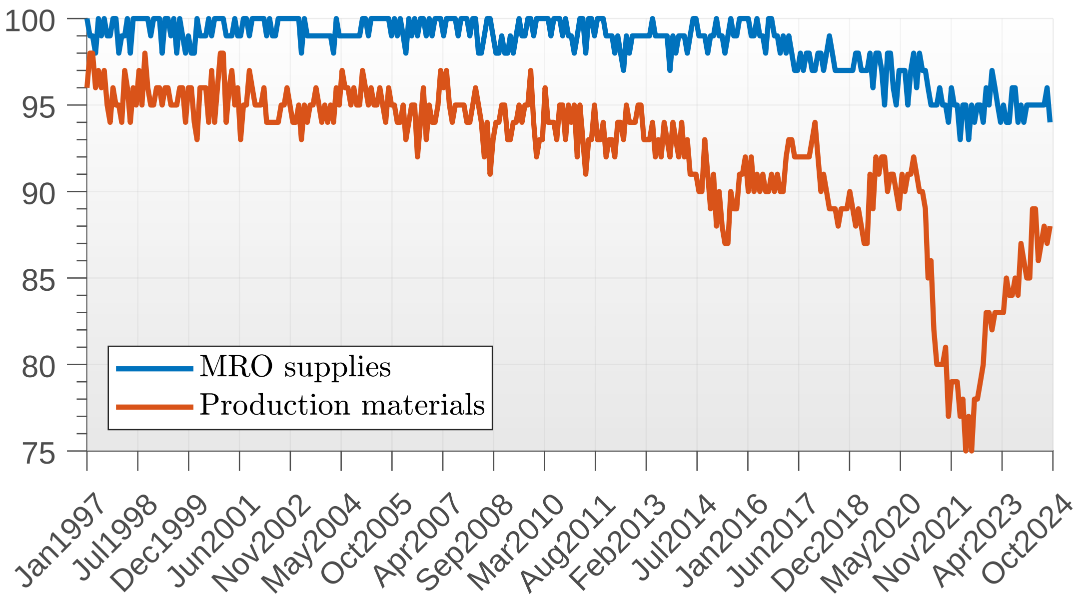

Figure 2: Share of delivery lead times ≤ 90 days. The figure shows data from the Institute for Supply Management (ISM) representing the percentage of firms reporting delivery lead times that are lower than 90 days.

one quarter since supply and demand disturbances occur. During our sample, an average 98.4% (92.0%) of MRO supplies (production materials) have been delivered within 90 days from the date the order was placed. As one can see, before March 2020 the figures were even higher, standing at 99.1% and 93.4% respectively. We thus conclude that there is strong evidence against estimating models like the one we propose with quarterly data, as firms are able to change their stock investment within that period thereby concealing and potentially biasing their estimated response to relevant shocks in a quarterly model.

3 Methodology

As we said, understanding whether inventory investment is driven by demand or supply shocks is of course of great interest. At the same time, inventories are also a forward-looking item that at times react relatively more to changes in *expectations* about what will happen in the next few months. We thus deem natural to assume inventory investments to be driven by shocks to current demand, expected demand, current supply, and expected supply.[11] As we will see, classifying disturbances in this way proves useful as two of those shocks generate positive inventory investments against negative news about

[11]Görtz et al. (2022) also recognize that "*Inventories have a strategic role in buffering anticipated and unanticipated supply and demand disturbances*".

Table 3: Sign restrictions

	Positive current demand	Positive expected demand	Negative current supply	Negative expected supply
Change in real nonfarm inventories	-	+	-	+
Industrial Production %MoM	+	+	-	+
Goods prices %MoM	+	+	+	+
Future General Business Activity	+	+	-	-

Cells filled with + (-) mean that a given shock exerts a positive (negative) impact effect on a specific variable.

the economy, and without a framework like the one we propose it is therefore hard to rationalize the sometimes counterintuitive fluctuations in inventories.

Table 3 reports the sign restrictions we impose. First, firms that underestimate sales in a given period are subject to a positive shock to current demand which obliges them to deplete inventories; goods prices increases in response, whereas firms learn about higher-than-expected sales in real time, so production increases within the month.[12] Second, firms that target a given inventory-sales ratio will respond to a positive shock to future demand by increasing inventories; the outlook for future activity improves. Third, a negative shock to current supply will prevent firms to expand production and lead them to draw on their inventory stock instead; goods prices increase. Fourth, a negative shock to expected supply - due e.g. to worsened expectations of supply chain bottlenecks developments or to increased geopolitical risks - will drive increased precautionary inventory investments and an increased Industrial Production, whereas the outlook for economic activity worsens.

The sign of the inventory response to supply conditions are consistent with those assumed in Crouzet and Oh (2016). As what concerns shocks to expected demand and supply, Blinder (1980) argues that holding inventories to protect against stockout risks or against higher expected prices is a very similar motive to hold inventories. Our assumptions make clear we depart from this thesis as we assume that higher expected demand has a different effect from lower expected supply for the first has a positive effect on future economic conditions, whereas the contrary is true for the latter.

Note that bad news about current demand and expected supply generate a positive investment in inventories and thus a positive contribution to GDP growth. In the next

[12]This corresponds to the case $\beta < 1$ in Blinder (1981), where β defines the degree with which firms buffer against unexpected sales shocks, with a lower β corresponding to higher shock absorption through higher production within the period.

section, we will relate each of those shocks to specific recent events and show actual examples where GDP growth was pulled down by negative inventory investments that were driven by good news, thereby blurring the real-time understanding of the GDP release. Our model clearly separates good news from bad ones, thus giving a clearer picture about the strength of economic activity.

4 Results

4.1 Demand or supply? Answering a long-dated question

As we said, the literature has long struggled to understand which of demand or supply are most important in driving inventory cycles, and we thus start the discussion of our results by reporting the Forecast Error Variance Decomposition (FEVD) of inventory investment in Table 4. As one can see from the table, demand shocks dominate the contemporaneous response of inventory investment, explaining 69.4% of the variation on impact, mainly thanks to current demand shocks which are the most important drivers of change in real nonfarm inventories at the very highest frequencies, being responsible for 39.2% of the Forecast Error Variance of change in real nonfarm inventories at $h = 0$, and declining afterwards. Jointly with the fact that inventories respond negatively to positive current demand shocks, this result is consistent with Blinder (1980) and Wen (2005) who find that inventories are highly countercyclical at very high frequencies. Wang et al. (2014) also finds that the role of transitory demand shocks is a driving force of the business cycle. Wen (2005) then argues that *"Since production can respond to demand shocks in the longer run, it reduces the impact of demand shocks on inventories"*.

Shocks to expected demand consistently explain a significant amount of variance throughout all horizons, giving support to Kahn (1987) stockout-avoidance theory whereby firms build up stocks in advance of an expected rise in sales. We also find that cost shocks have larger effects on relatively longer horizons. Precautionary investments driven by expectations of worsening supply conditions almost double their importance after three months, becoming the most important driver of inventory investment in the long run together with expected demand shocks.

The relevance of expected cost shocks is consistent with what found in Blinder (1986a) and Eichenbaum (1989), but contrasts with Ramey and West (1999) who state that it is rare to find statistically significant effects of observable measures of costs. Blinder and Maccini (1991) state that one explanation for the failure of the production smoothing model to explain why production is more variable than sales might lie in the existence of cost shocks that the firm observes before choosing output - our expected cost shocks. The authors argue that this might be enough to make output more variable than sales and to induce a positive correlation between inventory investment and sales, though they also acknowledge that the available empirical evidence is quite mixed. Again, our model reconciles theory with evidence by clearly showing that this relationship exists and is quite strong: the correlation between detrended sales and the historical decomposition of inventory investment driven by expected cost shocks is indeed positive and equal to 51.8%. Also, the result that supply shocks explain progressively more variance is consistent with Maccini et al. (2015), who find a slow speed of adjustment of inventories to a change in input costs.

Our framework can easily accommodate the empirical counterpart of the theoretical counterfactual experiment laid down in Blinder (1986a) where the author shuts down cost shocks and finds that the variance of production falls and drops below that of sales. First, we aggregate our monthly historical decompositions at a quarterly frequency. Second, we compute a counterfactual GDP series that excludes GDP variations driven solely by fluctuations in inventories caused by anticipated cost shocks. Third, we detrend GDP, GDP net of expected cost shocks, and final sales with the Hamilton (2018) filter. Finally, we compute standard deviations of the three cyclical components extracted from the abovementioned filtering procedure. When we do this, we find that the standard deviation of detrended GDP net of expected cost shocks (equal to \$446.8 billion) is indeed lower than that of detrended GDP (equal to \$482.2 billion) yet it is still slightly higher than the \$444.4 billion standard deviation of detrended sales. Recall however from the discussion in Section that another reason why production can be more variable than sales is because of expected demand shocks as in Kahn (1987). If we remove the effects of those shocks together with those from expected supply shocks as done above, the variance of detrended GDP net of expected demand and supply shocks drops to \$433.5 billion, lower than that that of detrended sales. Our results therefore provide clear empirical evidence for the important role of forward-looking news in exacerbating business cycle fluctuations.

Finally, Table 4 also shows that current supply shocks explain the least amount of variance, suggesting that firms do not get surprised very often by supply chain problems.[13] Moreover, current demand and expected supply shocks - i.e. those that generate positive investment against bad macroeconomic news - jointly explain more than half of the variation. This illustrates why inventory investments can be puzzling and at times hard to understand: our FEVD reveals that firms sometimes respond to unfavorable economic

[13]Nevertheless, we will see below that this was not true in the aftermath of the Covid-19 pandemic, and that our model captures well what happened in that period.

Table 4: FEVD of change in real nonfarm inventories

	Current Demand (CD)	Expected Demand (ED)	Current Supply (CS)	Expected Supply (ES)	CD+ED	CS+ES	CD+ES	ED+CS
$h = 0$	39.2	30.2	14.7	15.8	69.4	30.5	55.0	44.9
$h = 1$	30.8	26.5	18.6	24.2	57.3	42.8	55.0	45.1
$h = 2$	27.7	25.2	20.3	26.8	52.9	47.1	54.5	45.5
$h = 3$	26.4	25.8	20.1	27.7	52.2	47.8	54.1	45.9
$h = 6$	24.5	27.9	20.3	27.3	52.4	47.6	51.8	48.2
$h = 12$	23.3	29.8	20.5	26.4	53.1	46.9	49.7	50.3
$h = 24$	22.5	28.9	20.3	28.4	51.4	48.7	50.9	49.2
$h = 36$	22.3	28.7	20.6	28.5	51.0	49.1	50.8	49.3

The table shows the FEVD of change in real nonfarm inventories as a share of GDP at different horizons. The first four columns relate to our estimated shocks. The fifth (sixth) column reports aggregated FEVDs for demand (supply) shocks. The seventh (eighth) column reports aggregated FEVDs for shocks that on impact generate countercyclical (procyclical) responses.

news with positive investment.

4.2 An analysis of the role of current demand shocks

As widely discussed above, the literature long argued that - among other things - inventory investments are also driven by sales forecast errors, and our model attempts to capture this through the current demand shock. In this section we therefore want to validate our estimates by comparing them with retail sales surprises available from Refinitiv. The reason why we look at surprises on retail sales and not PCE is twofold. First, inventory investment only concerns goods, and retail sales predominantly cover goods.[14] The only service sector that is included in retail sales is "Food services and drinking places" which accounts for a share that increased from around 9% to 13% of total retail sales within our sample. Second, retail sales data are always published about two weeks before PCE data, meaning that the goods surprise component in PCE is to all practical purposes very small as PCE forecasts are updated after retail sales are released. In fact, PCE surprises are mainly driven by forecast errors in services consumption and to a smaller extent by those

[14] As stated by the Census Bureau (the federal agency that produces retail sales data): "*Retail Trade [...] includes establishments engaged in selling merchandise in small quantitites to the general public, without transformation, and rendering services incidental to the sale of merchandise*".

about inflation.[15]

In what follows as well as in the illustration of the historical decomposition that we show below we focus on the three-year subsample that started with the beginning of the pandemic emergency in March 2020 as in this period inventory investment was subject to very large fluctuations, and the role that the shocks we consider had is particularly clear. Figure 3 shows that the correlation between retail sales surprises and current demand shocks during this period is indeed very high, equal to 57.1%.[16] This is reassuring and makes us confident that our model is indeed able to disentangle properly the structural shocks we are interested in.[17]

Next, Figure 4 plots Impulse Response Functions (IRFs) of inventory investment to each of the four shocks. One can see that the response to a current demand shock is the only one whose impact effect dies out immediately and for all remaining horizons, which implies that the current demand Historical Decomposition (HD) for inventory investment will be highly correlated with current demand shocks, which is indeed the case as the two series correlate 95.5% in our full sample. Thus, this in turn implies that the current demand HD for inventory investment indeed purely reflects random sales forecast errors, which is a sensible result as firms very likely produce close-to-optimal sales forecasts.

If the contribution of current demand shocks purely reflects noise driven by unpredictable sales forecast errors, one can retrieve a series of "core" inventories that excludes the volatile historical decomposition stemming from a current demand shock from the series of inventory investment, which can be useful to better understand the state of the inventory cycle. Figure 5 plots this series. Apparently, core inventories are much less volatile than the original series, smoothing out very high-frequency movements that as we said above were driven by entirely unpredictable disturbances. Thus, the current demand contribution is an important and almost unpredictable factor that - if not properly accounted for - blurs our understanding of inventories and in turn of GDP growth. To further corroborate this, we ran a simple AR(1) regression of inventory investment and compared it with a regression of inventory investment on lagged *core* inventory investment as defined above. The R^2 we find is 40.2% in the first case and 51.0% in the second, confirming that core inventory investments predict next-period inventory investments

[15] Recall that retail sales are available only in current dollars, but that CPI data are always published before PCE, meaning that PCE inflation surprises are usually small and reflect the methodological differences that exist between CPI and PCE.

[16] For the whole sample, the correlation is equal to 38.0%. This lower correlation can be ascribed to the fact that - as recalled in Blinder (1981) - inventories play a rather minor role when the economy is expanding smoothly.

[17] Recall that a perfectly estimated current demand shock would still not be equal to retail sales surprises because the latter also include surprises related to goods inflation as well as to food services consumption.

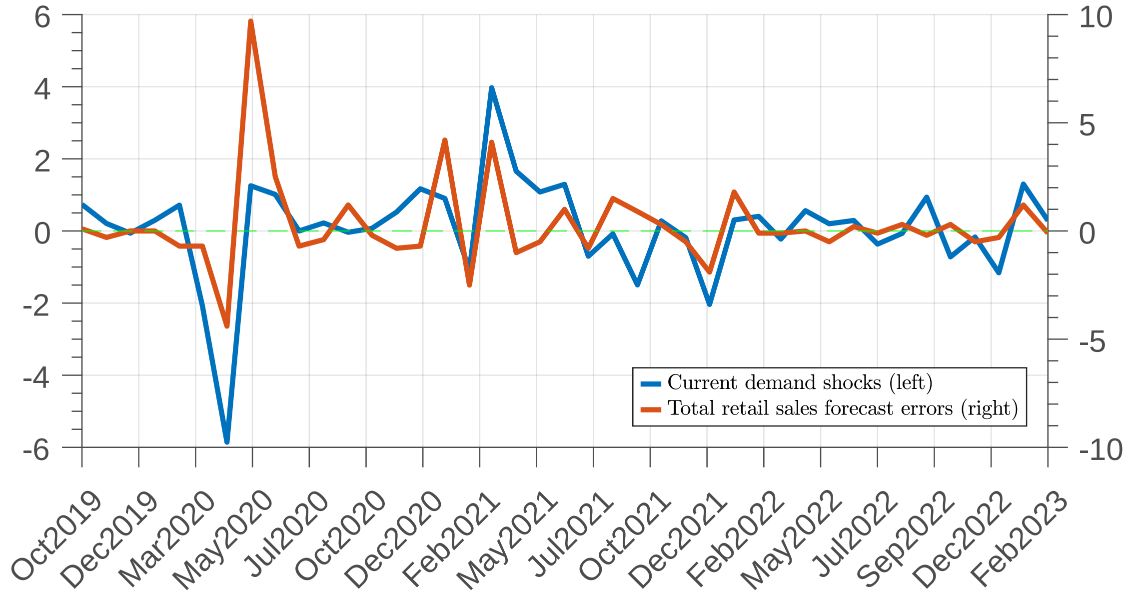

Figure 3: Current demand shocks and retail sales surprises. The figure plots current demand shocks together with retail sales surprises.

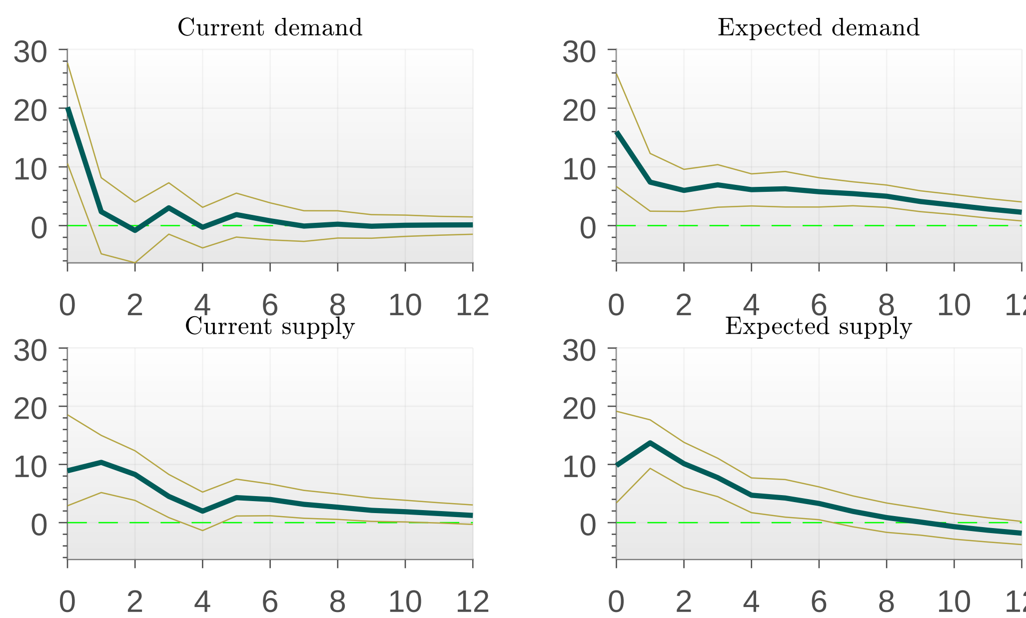

Figure 4: Impulse Response Functions. The figure plots Impulse Response Functions of change in real nonfarm inventories as a percentage of GDP after each of the four shocks we consider. Contrary to Table 3, and in order to show same-signed responses, IRFs for current demand (current supply) shocks are to be interpreted as responses to a negative (positive) shock.

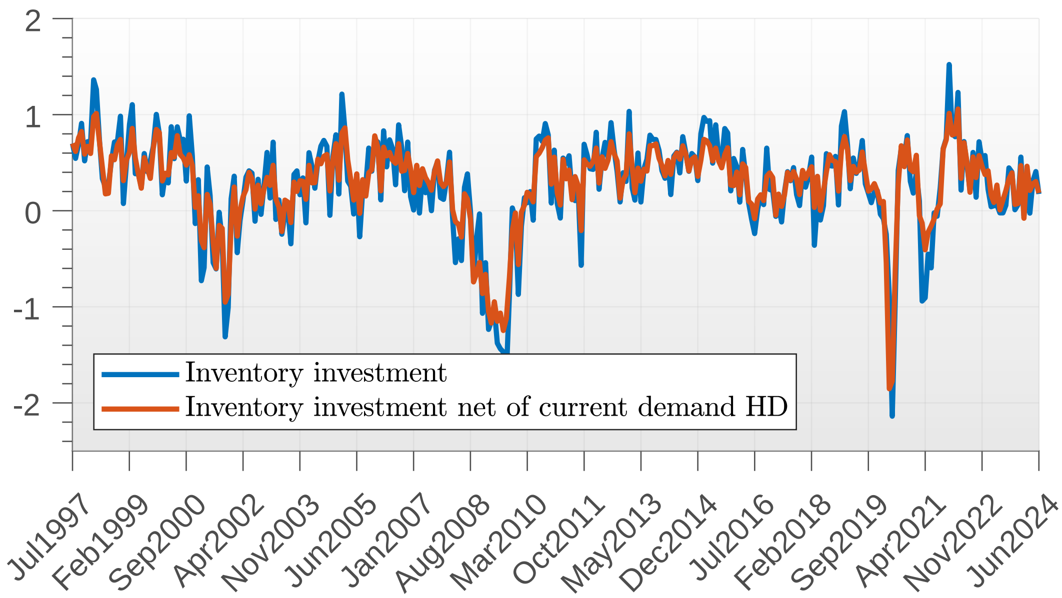

Figure 5: **Core inventories.** The blue line is the change in real nonfarm inventories as a percentage of GDP; the orange one plots the same series net of the current demand shock contribution obtained from the historical decomposition.

better than lagged inventory investments themselves by getting rid of estimated noise.

Our result of a high relevance of current demand shocks runs against what found in Blinder (1986a) where by looking at simple correlations between sales and inventory investments the author finds no evidence of a buffering motive for inventories. This is reiterated also in the review in Blinder and Maccini (1991). Thus, our findings shed light on a long-dated puzzle, showing that in order to uncover the negative correlation one really has to look at *unexpected* sales versus *unexpected* inventory investment as opposed to the raw series.[18]

4.3 Zooming into the post-pandemic period

Since the end of 2020, the recovery in global demand after the first pandemic waves surprised for its swiftness and strength, and it was mainly driven by the recovery in demand for goods. As a consequence, many firms that had initially revised their forecasts for new orders and investment plans downwards rapidly depleted their stocks and considerably increased their demand for intermediate goods to replenish their inventories. Moreover, the acceleration of the digitalization process triggered a rapid increase in the demand for

[18] To be fair, Blinder (1986a) does indeed also look at the correlation between unexpected sales and inventory investment, yet without unconvering a systematic negative relationship. Nevertheless, the author predicts sales with an autoregressive model rather than relying on surveys as we do here.

electronic devices and led to a scarcity of semiconductors, a component that is central in many sectors and for which expanding production capacity takes a relatively long time. Finally, demand-side pressures put transport and international logistics under strain, and prolonged ports closures in China due to the pandemic led to heavy congestion, longer shipping times and heightened freighting costs. Needless to say, inventories took center stage in this period, contributing at least twice as much to US GDP growth as what they did in the period from 1990 to 2019. We thus present results mainly for the period starting in 2020.

Figure 6 plots the Historical Decomposition of change in real nonfarm inventories as a percentage of GDP. In the immediate aftermath of the Covid shock in March 2020, both demand and supply collapsed as consumers refrained from buying goods and firms' productive possibility was heavily constrained by stay-at-home orders issued by the majority of US states, albeit with varying degrees of timeliness and restrictiveness. Our model finds indeed that negative demand and supply shocks moved inventories in opposing directions. Expectations of future re-openings as well as worsened expected demand moved inventories downwards, in both cases because of a lower need for precautionary investments in stocks. As can be seen from the yellow line, our model correctly finds that problems in supply chains already emerged at the end of 2020, worsened during 2021, and constituted a drag on stock build-ups at least until the end of 2022. The violet line shows instead that - once firms understood the relevance of this issue - they scrambled to replenish their stocks because of expectations of prolonged disruptions, a phenomenon that has been dubbed "bullwhip effect" and that lasted until the end of 2022. On March 2021, the huge fiscal stimulus provided by the American Rescue Plan Act led to an immediate very large and unexpected jump in goods consumption; our model finds that firms had to heavily draw from their stocks to meet heightened demand. Finally, the red line shows that the resilience of the economy led companies to update their sales forecasts and to ask for more inventories. This trend was abruptly interrupted by the start of the war in Ukraine in February 2022, where recessionary fears - compounded by expectations that the Fed monetary tightening would soon have had real effects - contributed to the disinvestment in inventories that was later observed throughout the year.

4.4 Mapping our estimates onto inventories contribution to GDP growth

The analysis proposed so far is based on a monthly decomposition of change in real nonfarm inventories. Nevertheless, interest many times hinges on the contribution of this component to GDP growth, since as we said inventory investment alone can change

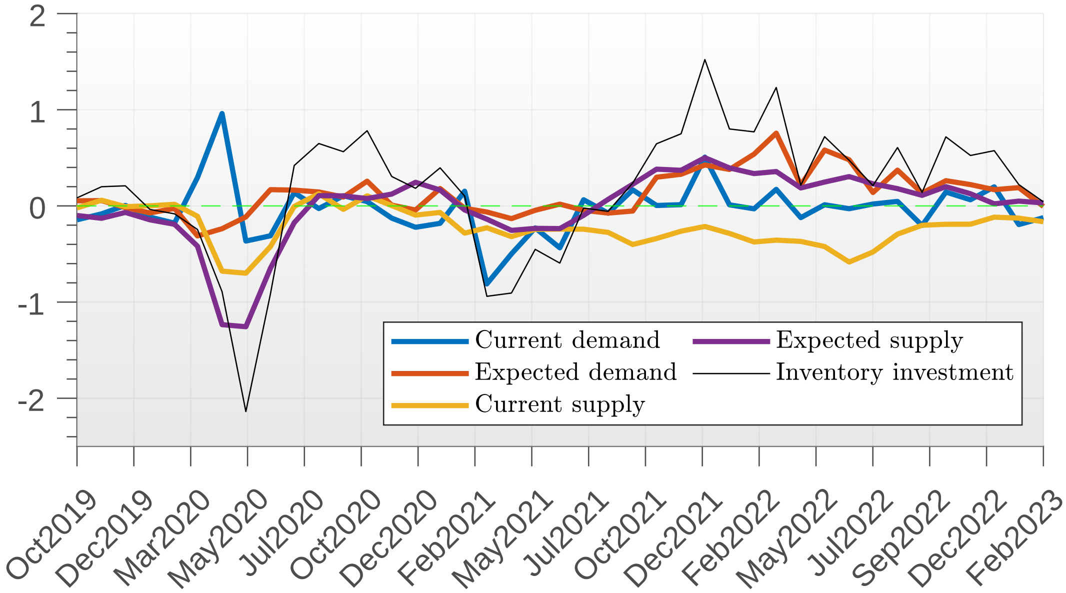

Figure 6: Historical decomposition of change in real nonfarm inventories. The figure plots the contribution of each of the four structural shocks to the observed realizations of change in real nonfarm inventories as a percentage of GDP.

our reading of the US economy without giving hints about whether a given contribution should be interpreted as a positive or negative development.

We provide a practical example that shows this issue and how our model helps clarifying certain situations. In 2023-Q1, the advance estimate of GDP reported a modest 1.1% quarterly annualized growth rate, whereas analysts polled by Consensus Economics were expecting almost twice as much an estimate, at 2.1%. The release showed that consumption was contributing a strong 2.5 percentage points, but inventories dragged growth by 2.3 percentage points. As Figure 7 shows, our model suggests that the main reason for the negative inventory contribution was due to a remarkably positive current demand shock that led firms to draw down their stocks. Indeed, January consumption was unexpectedly strong and predominantly driven by goods, recording a 1.0% increase over the *month*, the largest reading since the beginning of the series in 2007 if one excludes the period from May 2020 until March 2021. According to our model, this positive demand news alone led to a negative 1.4 percentage points contribution to GDP growth. Recall that in that period recessionary risks were deemed elevated, with analysts polled in the Federal Reserve Bank of Philadelphia Survey of Professional Forecasters estimating in the second quarter an average 45.2% probability of decline in GDP in the third quarter. Absent the aforementioned surprise, GDP growth would have been equal to 2.5%, a figure that would have better reflected the good performance of the US economy in the first quarter and in the

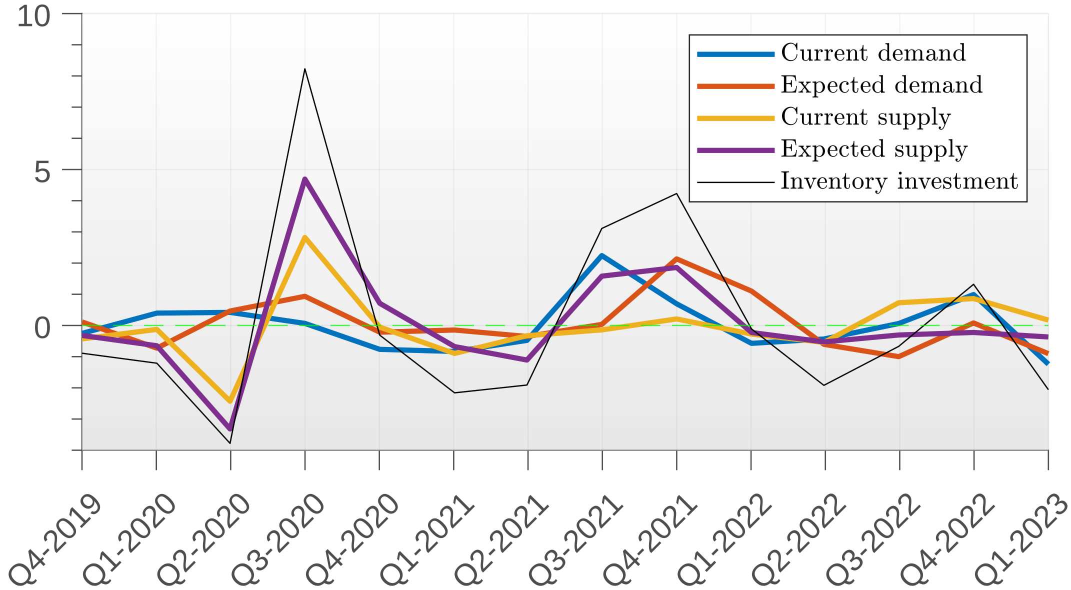

Figure 7: Change in real nonfarm inventories contribution to GDP growth. The figure plots the determinants of the contribution to GDP growth of change in real nonfarm inventories based on the assumed structural shocks in our model.

remainder of the year. Importantly, it seems also that professional forecasters fail to internalize the negative effects of positive consumption *surprises* on GDP growth, as the much higher forecasts for 2023-Q1 were likely indeed driven by the positive consumption data that were already available at the time the forecasts were made. Our results confirm previous suggestions in Mack (1957) that an anticipated positive consumption growth has a stronger effect on economic activity than an unanticipated one which rather leads to inventory disinvestments.

4.5 Sensitivity analysis

In this section we check whether our model estimates are robust to departures from the baseline specification, and we therefore estimate seven additional models. First, we add more lags to the VAR, going from six to nine and then twelve lags. Second, we substitute nonfarm inventories with manufacturing and trade inventories. Third, we substitute the goods PCE deflator alternatively with the PPI finished goods and with the PPI personal consumption goods. Fourth, we use the goods production Purchasing Managers Index from the Institute of Supply Management instead of Industrial Production. Fifth, we use the monthly growth rate of Industrial Production and that of the goods deflator rather than their log-levels. Finally, we estimate the model up to February 2020, thereby

Table 5: Robustness checks, whole sample

	Current Demand	Expected Demand	Current Supply	Expected Supply
9 lags	.979	.912	.984	.935
12 lags	.917	.917	.926	.919
Manufacturing and trade inventories	.979	.975	.993	.990
PPI finished goods	.919	.776	.733	.910
PPI personal consumption goods	.972	.939	.941	.984
ISM goods production	.775	.888	.874	.835
IP %MoM and goods PCE %MoM	.976	.981	.935	.965
pre-Covid	.837	.855	.859	.859

The table reports the correlations between the historical decomposition of change in nonfarm inventories in our baseline specification and those obtained from different models, using the entire available sample.

Table 6: Robustness checks, pandemic period

	Current Demand	Expected Demand	Current Supply	Expected Supply
9 lags	.979	.815	.984	.960
12 lags	.894	.814	.890	.963
Manufacturing and trade inventories	.986	.994	.990	.995
PPI finished goods	.938	.706	.767	.977
PPI personal consumption goods	.981	.950	.893	.995
ISM goods production	.769	.942	.848	.915
IP %MoM and goods PCE %MoM	.982	.993	.977	.986

The table reports the correlations between the historical decomposition of change in nonfarm inventories in our baseline specification and those obtained from different models, using only the observations between March 2020 and February 2023.

Table 7: Differences in FEVDs - baseline estimates versus pre-Covid

	Current Demand (CD)	Expected Demand (ED)	Current Supply (CS)	Expected Supply (ES)
$h = 0$	-5.0	-0.9	3.8	2.0
$h = 1$	-11.3	-3.4	6.1	8.7
$h = 2$	-13.2	-3.9	5.8	11.3
$h = 3$	-12.0	-2.9	3.6	11.2
$h = 6$	-8.7	-0.3	-0.4	9.4
$h = 12$	-7.8	0.9	-2.6	9.5
$h = 24$	-7.5	0.1	-2.9	10.4
$h = 36$	-7.3	1.0	-3.8	10.2

The table shows the difference between the FEVD of change in real nonfarm inventories obtained from our baseline model and from one that estimates parameters with data up to February 2020.

excluding the post-Covid period. Table 5 shows the correlations between the historical decompositions of inventory investment for all shocks and for all the different specifications. Apparently, our results are very robust as the lowest correlation equals 73.3% and the average correlation equals 91.4%. In addition, Table 6 shows that similar results apply if we compute correlations on the pandemic period only.

As what concerns the last robustness, in Table 7 we report the difference between the FEVD we obtain by estimating the model only with data up to February 2020 and the one from our baseline model. In this way we are able to gauge the extent to which the pandemic period is driving our findings related to the relevance of each of our shocks. The table shows that while expected demand and current supply shocks relevance remained very stable, the contribution of sales forecast errors after the pandemic became lower, partially substituted by an increased importance of expected supply shocks. In general, we believe that this result is not driven by Covid-related outliers and we thus deem that treating the most critical observations of the pandemic is not needed in our case: the only reduced-form residuals that exceed four standard deviations - an arbitrary but reasonable threshold for defining an outlier - are two: PCE goods prices in November 2008 and Industrial Production in April 2020. With 330 observations, two large outliers should have minimal impact on parameter estimates, also considering we are not using deterministic trends in the VAR. Moreover, according to the above definition of outlier, nonfarm inventories - our variable of interest - have none of them.

Conclusions

This paper provides an intuitive framework that allows to disentangle the drivers of investment in inventories and translate them in terms of contributions to GDP growth. Our model is useful for business cycle analysis, as inventory investment is an important yet as of today poorly-understood contributor to GDP growth. The model explains well recent events where inventory dynamics were hit by severe shocks, both persistent and transitory, and it finds that current demand shocks drive the highest share of stochastic fluctuations in inventories at very high frequencies. This component is almost unpredictable, driven by purely transitory sales forecast errors, and for this reason blurs our understanding of the inventory cycle and in turn of the business cycle. We then believe that by getting rid of it and focusing instead on core inventories as we define them in the paper one can obtain a better reading of the macroeconomy.

In the long run, we find that forward-looking economic conditions drive the largest share of fluctuations in inventories. Our model provides the first joint structural empirical evidence that explains why production is more variable than sales, corroborating previous theoretical insights that both expected cost as well as demand shocks could explain this classic puzzle.

The literature concerning inventories reaches back several decades, but in the past years interest in inventories dynamics faded. The pandemic period made clear that in turbulent and unpredictable times their role cannot be neglected.

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