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Faculty of Economics and Business Administration

The Role of Inventories in European Business Cycles: Evidence from 1999-2023

Jochen Hartwig
Sascha Keil

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Chemnitz University of Technology
Faculty of Economics and Business Administration
Thüringer Weg 7
09107 Chemnitz, Germany

Phone +49 (0)371 531 26000
https://www.tu-chemnitz.de/wirtschaft/index.php.en
wirtschaft@tu-chemnitz.de

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Abstract

This paper examines the role of inventories in macroeconomic fluctuations across 29 European countries from 1999 to 2023, covering three major recessions. Using a novel panel dataset and dynamic panel-econometric methods, we analyse short- and long-run inventory behaviour. Results confirm the broadly pro-cyclical nature of inventories but reveal a more complex dynamic: inventories are initially depleted in response to demand shocks, followed by restocking and, in some cases, systematic correction after four quarters.

During the Great Recession and Eurozone crisis, inventory depletion accounted for up to 80% of GDP losses, underscoring their amplifying role. In contrast, the COVID-19 recession featured limited de-stocking and earlier restocking, suggesting a structural shift in inventory strategies. These findings highlight inventories' dual role—as amplifiers or stabilizers—depending on the timing and nature of shocks, and call for greater attention to inventory dynamics in forecasting and policy design.

Keywords: Inventory investment, Production, Business cycles, Recessions in Europe

JEL classification: E22; E32; O52

Jochen Hartwig

jochen.hartwig@wiwi.tu-chemnitz.de

- *Department of Economics and Business Administration,*
  Chemnitz University of Technology, Chemnitz, Germany
- *KOF Swiss Economic Institute, ETH Zurich, Zurich, Switzerland*
- *Hans-Böckler-Stiftung, Forum for Macroeconomics and Macroeconomic Policies, Düsseldorf, Germany*

Sascha Keil

(corresponding author)

sascha.keil@wiwi.tu-chemnitz.de

- *Department of Economics and Business Administration,*
  Chemnitz University of Technology, Chemnitz, Germany

1. Introduction

Inventory investment is a key driver of short-run GDP fluctuations, amplifying economic cycles by depleting stocks during downturns and rebuilding them during recoveries (Ramey and West, 1999). Despite its recognized macroeconomic importance, understanding inventory dynamics remains challenging due to overlapping supply and demand effects, delays in firms' responses along supply chains, and limited access to reliable price-adjusted inventory data. Recent global disruptions, including the COVID-19 pandemic and rising geopolitical tensions, have raised uncertainty, demand volatility, and supply chain challenges, making inventory swings an increasingly critical factor in GDP dynamics. As economic volatility grows, unravelling the patterns of inventory cycles has become more urgent.

This paper is a follow-up to an earlier study by Abrahamsen and Hartwig (2011) that focussed on the dynamic pattern of inventory investment and production during the 'Great Recession' of 2008/09 in Europe. Extending their work, we examine whether these patterns persisted across three major recessions—the Great Recession, the Eurozone crisis, and the 2020 COVID-19 recession—using quarterly data from 29 European countries over the period 1999–2023. Unlike the earlier study, we employ both descriptive and inferential statistical methods, enabled by the expanded time frame, to provide a more robust analysis of inventory behaviour across a diverse set of European economies.

Over the past four decades, this literature – including Wilkinson (1989), Blinder and Maccini (1991a,b), Christodoulakis et al. (1995), Hornstein (1998), Wen (2005), and Chikán and Kovács (2009) – has uncovered two stylized facts: (i) inventory investment is positively correlated with sales and is thus amplifying macroeconomic cycles, and (ii) production is more volatile than sales. The previously prevailing 'production smoothing hypothesis', which suggested a counter-cyclical pattern since firms were assumed to hold inventories as buffer stocks to stabilise production, has thus been replaced (Chikán et al., 2018). Bec and Salem (2013) even consider inventory investment to be the dominant force driving GDP fluctuations. A particular role is assigned to inventories during recessions. Blinder and Maccini (1991a) and Hornstein (1998) point out that inventory disinvestment can account for up to 90% of output losses during recessions in the US.

While the consensus view is that inventory investment moves pro-cyclically with GDP, some studies continue to observe counter-cyclical inventory behaviour, attributing it to country- or sector-specific factors or to exceptional circumstances (Smith et al., 2006; Clausen and Hoffmaister, 2010; Cesaroni, 2011; Cakmakli et al., 2023). Particularly, the precise dynamic adjustment pattern of inventories relative to the economic cycle, including overlapping and delayed effects, remains unclear, which may help explain some of the exceptional findings. Empirical research focusing on the 2008/09 downturn shows that inventory depletion occurred with a delay of one to three quarters after the onset of the recession. Abrahamsen and Hartwig (2011) interpret this as evidence that inventory fluctuations amplify short-run macroeconomic movements in recessions but do not cause them. Moreover, Bec and Salem (2013) observe that in the US and in France, inventories tend to rebound systematically after the trough of the business cycle, acting as a driving force of the recovery.

Inventory research follows a cycle of its own. The strong recession triggered by lockdown measures in response to the COVID-19 pandemic and the subsequent recovery have once again brought inventories into focus. The past five years have been marked by volatile demand, geopolitical uncertainty, and supply-side challenges, including raw material price volatility and supply chain disruptions. Furthermore, this period has been shaped by a particular strong fiscal policy response (Heimberger, 2023). Aksoy et al. (2022) argue that these fundamental shifts in the economic environment have amplified the role of inventory investment as firms have sought to enhance resilience by increasing stock levels. While Cakmakli et al. (2023) present evidence that supply constraints have reinforced a counter-cyclical role of inventories, leading to a stabilising effect during the 2020 recession, Andersson and Le Breton (2022) argue that hoarding inventories may since have amplified the pro-cyclicality of inventory changes. Analysing the post-pandemic period, Rossi (2025) suggests that counter-cyclical inventory dynamics may dominate in the very short run as a reaction to sudden and unexpected demand shocks, while pro-cyclical patterns prevail in the longer run.

The assessment of inventory cycles remains a complex and puzzling subject. We argue that the difficulty in establishing a uniform pattern is rooted in three major challenges for empirical research. *First*, aggregate inventory fluctuations reflect overlapping effects. Inventory changes can result from active stocking behaviour by firms or passive, unintended fluctuations. These shifts depend on whether firms are responding to expected or unexpected changes in supply or in demand. *Second*, disentangling these effects is further complicated by lags in production adjustments stemming from changes in stocking behaviour. These delays occur both within firms and across supply chains, as illustrated by phenomena like the ‘bullwhip effect’.[1] *Finally*, lack of reliable data complicates empirical research in this area. Eurostat does not publish data on inventory investment in real terms; only nominal data are available for most countries.[2] In addition, recent inventory data have been prone to sometimes drastic revisions.

Our research into the role of inventory investment in economic cycles pursues two major goals. First, we assess the dynamic adjustment pattern of inventories across the business cycle. Second, we evaluate the strength of pro-cyclical inventory adjustments during recessions. To achieve these goals we construct a comprehensive panel dataset covering 29 European countries from 1999Q1 to 2023Q4. This time span allows to zoom in on three major economic downturns: the Great Recession (2008–

[1] The ‘bullwhip effect’ is a supply chain phenomenon where the variance in orders becomes amplified as you move upstream in the supply chain. The effect gets its name from the physics of cracking a bullwhip. When you swing a bullwhip, a small movement at the handle results in a much larger, amplified motion at the tip of the whip.

[2] This is because nominal inventory investment is negative during periods of depletion, which makes the construction of a real chained time series unpractical. Only the inventory *impulse* is available as a quarterly time series in real terms. The inventory impulse measures the change in inventory investment or, in other words, the second derivative of the aggregate level of inventories, in relation to GDP.

2009), the Eurozone crisis (2010-2015, primarily affecting Southern Europe), and the brief but severe COVID-19 recession (2020). Our dataset is enriched with two self-computed series: 'inventory intensity' and aggregate final sales. Analysing this large dataset with panel-econometric techniques to provide evidence on the dynamic response of aggregate inventory investment to GDP shocks is our key contribution to the literature.

The paper is organised as follows. Section 2 discusses our dataset including its limitations. Section 3 explains the various dynamic estimation techniques used in the empirical analysis and presents the results. We first explore the dynamic adjustment of inventories to the business cycle in section 3.1, investigating at which point in time during recessions inventory adjustments occur and whether these adjustments amplify or smooth GDP fluctuations. Subsequently, we focus on inventory behaviour during the last three European recessions in section 3.2, assessing general inventory patterns in downturns and the heterogeneity across countries and episodes. Section 4 concludes.

2. Data

Our empirical investigation draws on national accounts data from Eurostat, covering 29 countries and the period 1999Q1 to 2023Q4. Table 1 provides a detailed overview of the quarterly variables, units, and price adjustments. In addition to using Eurostat data on inventory changes, real GDP, and industrial production, we enrich our empirical analysis by computing additional time series for what we call the 'inventory intensity' and aggregate final sales following Abrahamsen and Hartwig's (2011) methodology. Inventory intensity is the ratio of changes in inventories to GDP, both expressed in real terms ($\Delta N^{py-1}/GDP^{py-1}$). The underlying computation relies on series expressed at previous year's prices, ensuring additivity of GDP expenditure components and enabling meaningful decomposition. Inventory investment at previous year's prices results according to Equation 1.

$$(1) \qquad \Delta N_{q,y}^{py-1,sa} = GCF_{q,y}^{r,sa} \frac{\sum_{i-1}^{4} GCF_{i,y-1}^{nom,orig}}{\sum_{i-1}^{4} GCF_{i,y-1}^{r,orig}} - GFCF_{q,y}^{r,sa} \frac{\sum_{i-1}^{4} GFCF_{i,y-1}^{nom,orig}}{\sum_{i-1}^{4} GFCF_{i,y-1}^{r,orig}}$$

ΔN is inventory investment, *GCF* gross investment and *GFCF* gross fixed investment; *py-1* stands for previous year's prices, *sa* for seasonally adjusted, *q* for quarter, *y* for the current year, *y-1* for the previous year, *r* for real, *nom* for nominal and *orig* for not seasonally adjusted.

Based on the same approach, we compute a time series for final sales (*X*) by aggregating the expenditure components final consumption (*C*), gross fixed investment and net exports (*EX – IM*) (see Equation 2). Like most European statistical offices, we use the 'annual overlap' method for the chaining procedure of this series (see von der Lippe and Küter, 2005). The quarterly data at previous year's prices are linked to the mean of the previous year's volume figures.

$$X_{q,y}^{py-1,sa} = C_{q,y}^{r,sa} \frac{\sum_{i-1}^{4} C_{i,y-1}^{nom,orig}}{\sum_{i-1}^{4} C_{i,y-1}^{r,orig}} + GFCF_{q,y}^{r,sa} \frac{\sum_{i-1}^{4} GFCF_{i,y-1}^{nom,orig}}{\sum_{i-1}^{4} GFCF_{i,y-1}^{r,orig}} + EX_{q,y}^{r,sa} \frac{\sum_{i-1}^{4} EX_{i,y-1}^{nom,orig}}{\sum_{i-1}^{4} EX_{i,y-1}^{r,orig}} - IM_{q,y}^{r,sa} \frac{\sum_{i-1}^{4} IM_{i,y-1}^{nom,orig}}{\sum_{i-1}^{4} IM_{i,y-1}^{r,orig}} \tag{2}$$

As already noted in the Introduction, European inventory data are not impeccable. Inventories are among the least trustworthy components of GDP.[3] Most recently, inventory data have been highly prone to revisions and do often serve as a balancing item, absorbing revisions in other expenditure-side components to maintain stable quarterly GDP estimates (Asimakopoulos et al., 2023). However, our objective is to exploit the strengths of a large and long panel dataset, which offers significant compensating advantages. It increases statistical power, allows for the identification of broader empirical regularities, and enables the use of robust estimation techniques that can mitigate the effects of noisy individual series. By varying key variables and employing complementary methods, we aim to ensure that our findings are not driven by measurement issues.

Table 1: List of variables

Variable name	Symbol	Description	Unit and price adjustment method
Inventory impulse	NI		P.p. contribution to GDP growth
Real GDP	Y	Output approach	Real 2015 Euros (chain-linked)
Real Sales	X	$C + GFCF + EX - IM$	Real 2015 Euros (chain-linked)
Industrial production	IP		Index (2015=100)
Changes in inventories	ΔN		Real 2015 Euros (chain-linked), Deflator: Implicit GFCF
Change in real GDP	ΔY		Real 2015 Euros (chain-linked)
Inventory intensity	IN	$\Delta N / Y$	Real Euros (previous year-price base)
Growth rate of real GDP	$\Delta logY$		Percent to previous quarter

Source: https://ec.europa.eu/eurostat/web/national-accounts/database and own calculations

3. Empirical assessment

Section 3.1 examines the dynamic adjustment of inventories relative to the business cycle by means of inferential statistical methods while section 3.2 descriptively assesses the strength of inventory depletion during economic recessions.

3.1. The dynamic adjustment pattern

This section looks for a general dynamic adjustment pattern of how inventories co-move with aggregated economic activity. To ensure the robustness of our findings, we econometrically assess the relationship between inventory dynamics and the business cycle using multiple specifications in different dynamic panel data models. Specifically, we analyse both the inventory impulse and changes in inventories. These variables differ. Inventory investment is an expenditure-side

[3] Given the challenges with inventory data availability and reliability, empirical research faces some limitations. For example, broad price deflators must be applied to some nominal series. However, robustness checks using various variables such as inventory intensity and aggregate final sales suggest that these limitations do not compromise our findings.

component in national accounts, while the inventory impulse is a pure residual: the difference between the growth contributions of the other expenditure components and GDP growth. As explanatory variables capturing business cycle dynamics, we use both demand-side and supply-side indicators. These include time series for final sales, aggregate output, and industrial production.

3.1.1. Econometric methodology

In the first exercise we estimate dynamic panel models with two-way fixed effects (following Baltagi, 2021) using OLS to identify the short-run adjustment patterns of inventories relative to the business cycle. In other words, we model the dynamic response of inventories to business cycle fluctuations while controlling for unobserved country- and time-specific heterogeneity. The inclusion of lagged output terms accounts for possible delayed adjustment effects, which are typical in inventory behaviour due to production and ordering frictions. Lag (l) structure is determined by applying a general-to-specific approach, starting with a maximum of 10 quarterly lags, and selecting the optimal model based on the Akaike information criterion. The model regresses the inventory impulse (NI) on an autoregressive term, the first difference in real output (Y) or, alternatively, industrial production (IP), and includes country-specific (μ) and time-specific (λ) fixed effects:

$$(3) \qquad NI_t = c + \alpha NI_{t-1} + \sum_{i=0}^{l} \beta_i \Delta Z_{t-i} + \mu_i + \lambda_t + \epsilon_t \quad \text{where} \quad Z \in \{Y, IP, X\}$$

Moreover, in a second exercise, we are interested in the potentially distinct short- and long-run behaviour of inventories. In this context, autoregressive distributed lag (ARDL) models offer a suitable framework for capturing dynamic patterns relative to the business cycle. This class of models explicitly accounts for the long-run relationship between the variables under scrutiny and provides insights into how the short-run adjustment process towards equilibrium unfolds. However, due to the non-availability of chained time series for inventory investment (and their probable stationarity if they were available), standard econometric techniques that focus on long-run relationships—such as ARDL cointegration methods—cannot be applied. These techniques typically require the dependent variable to be non-stationary. Nevertheless, given the usefulness of such methods in this research context, we adopt a workaround by regressing the non-stationary I(1) time series for real aggregate production on real aggregate sales, allowing for an assessment of the co-movement of both aggregates. Since the difference between the two is equivalent to changes in inventories, this substitution indirectly captures inventory dynamics. Hence, this approach enables us to: (i) employ advanced long-run regression techniques, (ii) infer about inventory behaviour without using an (unavailable) real inventory variable, and (iii) generate evidence based on consistent real-term time series for each panel unit. Following the notation of Blinder and Maccini (1991a), changes in inventories (ΔN) are defined as the difference between aggregate production (Y) and aggregate final sales (X): $\Delta N_t = Y_t - X_t$. In this way, we aim to infer on the systematic dynamic adjustment process of production following a shock in sales, thereby revealing underlying inventory behaviour.[4] The ARDL model is estimated in error correction form (Equation 4), where the short-run coefficients capturing the behaviour following sales fluctuations are denoted by the β_i terms, and the adjustment coefficient by α. The long-run coefficient is calculated as $-\eta/\alpha$. The ARDL lag structure is denoted by p and q.

$$(4) \qquad \Delta logY_t = c + \alpha logY_{t-1} + \eta logX_{t-1} + \sum_{i=1}^{p} \beta_i \Delta logY_{t-i} + \sum_{j=0}^{q} \gamma_j \Delta logX_{t-j} + \epsilon_t$$

Following the approach described by Blackburne and Frank (2007), we estimate three distinct panel ARDL models by means of the maximum likelihood method that differ in how they handle cross-sectional heterogeneity. A Mean Group model (MG) is employed first, allowing for heterogeneity of all regression parameters in the error correction model. If slope heterogeneity is an issue only for the short-run regressors, the preferable technique is the pooled mean group model (PMG). Here, the long-run coefficients are constrained to be homogeneous while short-run dynamics, error variances, and intercepts are allowed to vary across cross-sections. Finally, a dynamic fixed effects model (DFE) is employed. This model is less appropriate in case of strong panel heterogeneity, since it allows only for heterogeneous intercept and adjustment terms while all other coefficients are restricted to be homogenous.

3.1.2. Results

Table 2 presents the results of our first econometric exercise. The left two tables display the key coefficients from the dynamic models, in which the inventory impulse is regressed on either real output (Models 1.1–1.3) or industrial production (Models 2.1–2.3). As the inventory impulse cannot be expressed in logarithmic terms, coefficients are not interpretable as elasticities. The positive and statistically significant coefficients in the initial quarters following a positive change in production underscore a pro-cyclical pattern. However, starting from the third or fourth quarter, sometimes negative coefficients emerge, indicating a corrective effect that persists for up to seven quarters. Interestingly, this finding appears related to aggregate factors affecting all panels units, since the corrective effect largely disappears when considering time fixed effects.

The right table presents the main coefficients employing aggregated sales as explanatory variable (Models 3.1–3.3). The key difference is the contemporaneously negative inventory effect. A shock to production (Models 1.1 – 2.3) leads to unambiguously pro-cyclical inventory behaviour while a shock to aggregate sales is associated with a contemporaneous reduction in the inventory impulse and a lagged pro-cyclical pattern.

[4] We actually estimate the linear long-run relationship $Y_t = c + \beta X_t + \epsilon_t$, where $Y_t = X_t + \Delta N_t$. After transformation, this model is equivalent to $\Delta N_t = c + (\beta\text{-}1) X_t + \epsilon_t$. Hence, deducting 1 from the estimated β will inform on how inventories co-move with aggregate final sales. This exercise is explicitly restricted to assessing co-movement, thus sidestepping the simultaneity issue that would arise when attempting causal interpretation of the estimates.

Table 2: Central regression coefficients from dynamic models

TWFE / DV: Inventory Impulse				
		1.1	1.2	1.3
Variable			FE	TWFE
AR	L1	-0.42***	-0.421***	-0.429***
		(0.029)	(0.029)	(0.030)
Y	D	+0.068***	+0.07***	+0.060**
		(0.020)	(0.019)	(0.028)
	LD	+0.049***	+0.051***	+0.021
		(0.015)	(0.014)	(0.029)
	L2D	+0.036	+0.039**	+0.028
		(0.016)	(0.010)	(0.014)
	L3D	+0.007	+0.009	-0.003
		(0.009)	(0.010)	(0.014)
	L4D	-0.065***	-0.063***	-0.045*
		(0.020)	(0.021)	(0.024)
	L5D	-0.041**	-0.039**	-0.0185
		(0.016)	(0.017)	(0.030)
	L6D			+0.007
				(0.026)
	L7D			+0.042*
				(0.021)
Stat.	n	2769	2769	2711
	c	29	29	29
R2	Within	0.19	0.18	0.23
	Between	0.46	0.43	0.41
	Overall	0.19	0.18	0.23
Test	Wald χ	450.87***		
	F test		61.48***	17.35***

TWFE / DV: Inventory Impulse				
		2.1	2.2	2.3
Variable			FE	TWFE
AR	L1	-0.43***	-0.431***	-0.439***
		(0.027)	(0.027)	(0.029)
IP	D	+0.042***	+0.043***	+0.006
		(0.010)	(0.010)	(0.015)
	LD	+0.053***	+0.054***	+0.042***
		(0.009)	(0.009)	(0.011)
	L2D	+0.021**	+0.022**	
		(0.010)	(0.010)	
	L3D	-0.011	-0.009	
		(0.009)	-(0.031)	
	L4D	-0.033***	-0.031***	
		(0.009)	(0.009)	
	L5D	-0.017**	-0.016*	
		(0.008)	(0.009)	
	L6D	-0.003	-0.002	
		(0.011)	(0.011)	
	L7D	-0.019*	-0.017*	
		(0.009)	(0.009)	
Stat.	n	2490	2490	2664
	c	29	29	29
R2	Within	0.20	0.20	0.25
	Between	0.52	0.48	0.50
	Overall	0.20	2.00	0.25
Test	Wald χ	663.89***		
	F		74.99***	13.46***

TWFE / DV: Inventory Impulse				
		3.1	3.2	3.3
Variable			FE	TWFE
AR	L1	-0.323***	-0.32***	-0.296***
		(0.030)	(0.030)	(0.029)
X	D	-0.338***	-0.336***	-0.531***
		(0.043)	(0.044)	(0.064)
	LD	+0.010	+0.010	-0.039**
		(0.013)	(0.014)	(0.015)
	L2D	+0.102***	+0.100***	0.101***
		(0.015)	(0.016)	(0.016)
	L3D	+0.044***	+0.038***	+0.068***
		(0.011)	(0.013)	(0.015)
	L4D	-0.019*	-0.022*	+0.054***
		(0.011)	(0.012)	(0.013)
	L5D		-0.002	+0.054***
			(0.016)	(0.018)
	L6D		-0.023*	
			(0.014)	
	L7D			
Stat.	n	2798	2740	2769
	c	29	29	29
R2	Within	0.43	0.43	0.43
	Between	0.19	0.19	0.17
	Overall	0.43	0.43	0.43
Test	Wald χ	446.98***		
	F		97.05***	66.34***

*Y: Real GDP, IP: Real industrial production, X: Real sales, D: Difference, L: Lags. Robust standard errors in parentheses. Critical values: 1% ***; 5% **; 10% *. Period: 1999Q1-2023Q4. Explanatory variables are expressed in index (2015=100) terms. In case of TWFE a joint F test of the time effects is carried out.*

Table 3 shows the panel ARDL results. Both real output and real sales are expressed in logs, enabling elasticity interpretation. Given the strong long-run relationship between output and final sales, we expect the long-run coefficient to approach unity—an expectation confirmed by both the MG and PMG models. The failure of the DFE model to replicate this result highlights the importance of accounting for panel heterogeneity in the short-run dynamics. Considering the short-run adjustment toward this equilibrium, we find that immediately after a 1% sales shock aggregate production increases by around 0.8%, implying a contemporaneous inventory depletion—a dynamic that contributes to business cycle smoothing. In the subsequent two quarters, however, production rises by 0.4% and around 0.1%, respectively, reflecting the pro-cyclical restocking that amplifies the cycle. Notably, production goes down after four quarters, which may reflect a systematic bouncing-back effect, as discussed by Bec and Salem (2013). However, this correction appears to represent a reversion toward the long-run equilibrium, as the short-run pro-cyclical response of aggregate production temporarily exceeds the increase in final sales.

Table 3: Central regression coefficients from dynamic panel ARDL models

		ARDL / DV: Real Output		
		4.1.	4.2.	4.3.
Variable		MG	PMG	DFE
ADJ		-0.491***	-0.475***	-0.484***
		(0.017)	(0.021)	(0.015)
X	D	+0.792***	+0.772***	+0.690***
(s-r)		(0.030)	(0.035)	(0.016)
	LD	+0.425***	+0.416***	+0.404***
		(0.021)	(0.022)	(0.019)
	L2D	+0.074***	+0.083***	+0.112***
		(0.021)	(0.021)	(0.017)
	L3D	-0.016	-0.005	+0.051***
		(0.020)	(0.019)	(0.017)
	L4D	-0.08***	-0.075***	-0.014
		(0.022)	(0.020)	(0.016)
	L5D	-0.078***	-0.074***	-0.014
		(0.021)	(0.020)	(0.017)
	L6D	-0.074***	-0.073***	-0.041**
		(0.016)	(0.017)	(0.016)
	L7D	-0.044***	-0.043***	-0.028*
		(0.011)	(0.012)	(0.016)
X	L	+0.973	+0.992	+0.885
(l-r)		(0.017)	(0.002)	(0.007)
Stat.	n	2711	2711	2711
	c	29	29	29

X: Real sales, D: Log difference, L: Lags
Standard errors in parentheses.
*Critical values: 1% ***; 5% **; 10% *. Period: 1999Q1-2023Q4*

Despite their notable differences, all approaches reveal a consistent pattern. Inventories generally tend to move pro-cyclically with respect to aggregate economic activity, albeit with a certain time lag. On aggregate, firms restock in upturns and deplete inventories during downturns. This adjustment process spans several quarters. In the very-short run, however, inventories are depleted after a positive sales shock, indicating a counter-cyclical reaction. Subsequently, a transition to the general pro-cyclical pattern follows. This finding is in line with Rossi (2025), who argues that unanticipated demand shocks—typically the dominant driver of high-frequency inventory changes—lead to immediate drawdowns in aggregate stock levels. Overall, our analysis highlights the empirical complexities in this field and underscores the importance of accounting for the temporal structure of inventory adjustments when evaluating their macroeconomic role.

3.2. Inventory depletions in European recessions

Beyond their complex cyclical dynamics, inventory changes play a critical role during economic downturns, when inventory sell-offs meet production stops. In this section, we explore inventory behaviour across different recessions in European countries. Specifically, we provide a comprehensive assessment of the strength of inventory adjustments and the timing of inventory depletion in the aftermath of a recession.

In line with Blinder and Maccini (1991a) and Hornstein (1998), we first calculate GDP losses and reductions in inventories to evaluate the strength of the pro-cyclical inventory pattern and its role in shaping the depth of European recessions. GDP losses are linked to inventory reductions observed during the recession and up to two quarters after the GDP trough.[5] Following Newson (2009), we

[5] This choice is based on the estimation results above (Models 1.1-2.3) indicating that pro-cyclical inventory reactions mainly take place up to two quarters after a GDP shock.

define an economic downturn as the period from the start of the decline to the quarter of the GDP trough. Therefore, a quarter with an increase in GDP still belongs to the contraction period if it is followed by a quarter in which GDP declines again, provided that the decline is more pronounced than the previous increase.

Table 4: Aggregated losses in output and inventories in recessions, in million Euros (in 2015 prices)

	Great Recession					Eurozone crisis					C19 Recession				
	ΔY		ΔN			ΔY		ΔN			ΔY		ΔN		
Country (c)	Σ€	(l)	Σ€	(l)	Ratio	Σ€	(l)	Σ€	(l)	Ratio	Σ€	(l)	Σ€	(l)	Ratio
Austria	-4030	8	-542	1	0.13						-12874	2	-786	2	0.06
Belgium	-3613	3	-1510	2	0.42	-570	5	-57	1	0.10	-14860	2	-1668	2	0.11
Bulgaria						-141	5	-100	1	0.71	-728	1	-64	1	0.09
Croatia	-1100	5	-576	3	0.52	-461	11	-1080	12	2.34	-1950	2	-222	1	0.11
Cyprus	-144	5	-235	2	1.63	-612	14	-343	13	0.56	-710	2	-476	1	0.67
Czechia	-2352	3	-1578	3	0.67	-695	5	-692	5	100	-5894	2	-1591	3	0.27
Denmark	-4926	6	-2619	4	0.53	-171	2	-27	1	0.16	-5058	2	-608	1	0.12
Estonia	-965	4	-363	4	0.38						-437	2	-298	3	0.68
Finland	-4982	3	-3263	5	0.65	-1605	5	-1534	4	0.96	-3840	2	-122	1	0.03
France	-21407	4	-14547	3	0.68	-2322	1	-709	1	0.31	-98474	2	-900	2	0.01
Germany	-51058	4	-10561	2	0.21	-6568	2	-2596	1	0.40	-90505	2	-5850	1	0.06
Greece	-3408	2	-5634	4	1.65	-9006	9	-787	2	0.09					
Hungary	-2155	6	-2152	4	1.00						-4984	2	-482	1	0.10
Ireland	-7060	8	-3366	8	0.48	-1001	5	-557	2	0.56					
Italy	-34373	5	-10253	4	0.30	-24617	9	-14768	7	0.60	-75198	2	-8628	2	0.11
Latvia	-1503	6	-62	1	0.04						-697	2	-219	4	0.32
Lithuania	-1494	6	-1570	5	1.05						-642	2	-2362	4	3.68
Luxembourg	-926	4	-993	4	1.07	-37	1	-69	1	1.86					
Malta						-35	2	-37	4	1.05					
Netherlands	-7767	4	-3205	3	0.41	-3288	8	-1190	6	0.36	-18127	2	-548	1	0.03
Poland						-375	2	-551	1	1.47	-11902	1	-957	1	0.08
Portugal	-2100	5	-936	3	0.45	-3583	8	-928	7	0.26	-9371	2	-492	2	0.05
Romania	-3813	1	-1044	1	0.27	-1251	2	-528	4	0.42	-5457	2	-1539	2	0.28
Slovakia	-1745	1	-374	3	0.21						-2221	2	-1063	2	0.48
Slovenia	-951	4	-236	4	0.25	-321	5	-217	3	0.68	-1372	2	-272	1	0.20
Spain	-12376	3	-2962	1	0.24	-13631	11	-3353	7	0.25	-66639	2	-357	2	0.01
Sweden	-6882	7	-7288	5	1.06	-1780	1	-598	2	0.34					
Switzerland															
United Kingdom	-36861	5	-32999	6	0.90	-1339	1	-3760	2	2.81	-149469	2	-10465	1	0.07
		4.5		3.4	0.61		4.9		3.8	0.87		1.9		1.8	0.33

Aggregated losses in terms of GDP (ΔY) accompanied by inventory depletions (ΔN) in three recessionary periods. Great Recession: 2008q1-2010q2; Eurozone crisis: 2011q1-2014q4; C19 Recession: 2020q1-2020q4. (l) indicates the number of quarters.

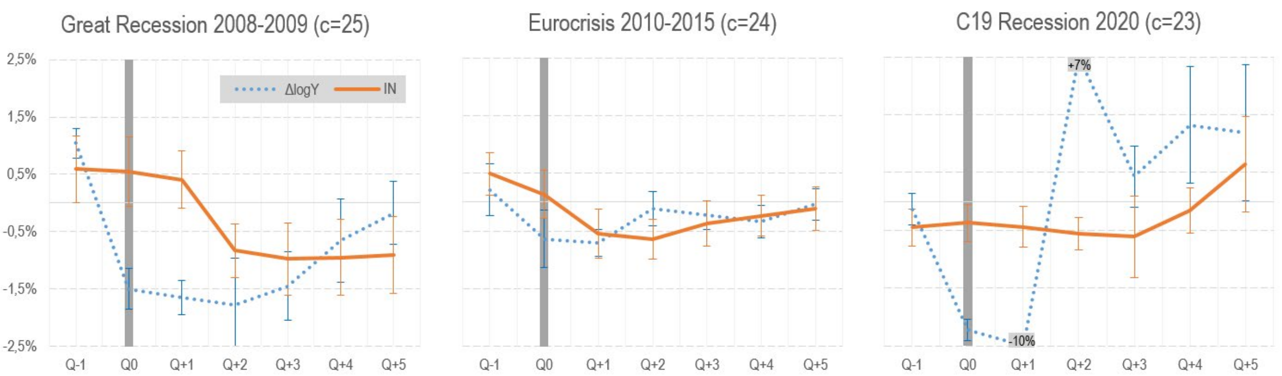
Table 4 presents the aggregated losses (in real Euros) and the duration of the respective recessions and inventory depletion periods (in quarters). The table shows how inventories responded to output contractions across downturns.[6] On average, inventory depletion during the Great Recession and the Eurozone crisis accounted for 61% and 87% of the corresponding GDP losses, respectively, underlining the strong pro-cyclical nature of inventory adjustments during these periods. During the Great Recession, larger economies (Germany, France, Italy, Spain) generally exhibited less pronounced inventory depletion relative to their GDP decline. In contrast, smaller economies such as Luxembourg, Lithuania, and Cyprus displayed a higher ratio. During the Eurozone crisis, Central and

[6] A more detailed illustration of the linked GDP losses and inventory depletions is given in Table A1 in the Appendix.

Eastern European countries (notably Poland, Czechia, Estonia, and Croatia), experienced particularly strong inventory adjustments.

By contrast, the inventory response during the COVID-19 recession was much weaker, averaging only 33% of the corresponding GDP loss. Compared to earlier recessions, this divergence may reflect structural changes in supply chains, differences in policy responses, or the unique nature of the COVID-19 shock and the strength of the countercyclical fiscal policy (Heimberger, 2023). It also points to a potential shift in corporate stocking behaviour toward more stabilizing inventory strategies. Once again, the larger countries displayed contained dynamics. In Germany and France for example, inventory reductions accounted for merely 1% and 6% of output losses, respectively — indicating a fundamentally different adjustment pattern. Conspicuously, Switzerland stands out: across all three recessions, no clear inventory depletion can be identified in response to GDP contractions — indicating either a very distinct production structure or simply poor data quality.[7]

Figure 1: Inventory Adjustment after the start of a recession



Panels show the average percentage point deviation from the periodical mean. Q0 indicates the start of the recession. Measure of dispersion: 90% Confidence interval. Periodical means: 2007q1-2010q4 (Great Recession), 2010q1-2014q4 (Eurozone crisis), 2019q1-2021q4 (C19 Recession).

The structural change in inventory behaviour is further highlighted in Figure 1, which displays real GDP growth rates alongside the inventory intensity, both computed using values at previous year's prices (see section 2 above). The figure shows the average deviation across European countries of the actual values from the periodical mean of GDP growth (blue dotted line) and inventory intensity (orange line) in the quarters before and after the onset of three major recessions. Q0 marks the beginning of each downturn.

During the Great Recession of 2008–2009, GDP growth dropped sharply in the 25 affected countries: to 1.5 percentage points on average below the mean growth rate in the starting quarter (typically 2008Q2 or Q3). It continued to decline until Q+2 and began recovering from Q+3 onward. Inventory intensity followed with a lag, starting to decline in Q+1, and falling to around 0.8

[7] In the fourth quarter of 2012, Switzerland experienced a minor GDP decline (-86 mln. Euro) connected to an intense inventory depletion (-6519 mln. Euro). Since $\Delta N/\Delta Y$ is more than 75, this episode is excluded from the analysis to avoid distortion of the results. Hartwig (2008) and Abrahamsen and Hartwig (2011) have already raised concern over the quality of Swiss macroeconomic data.

percentage points below the average, where it remained over the following quarters. Interestingly, GDP recovered from Q+3, while inventories did not in the considered time frame.

The Eurozone crisis of 2010–2015 displayed a less intense, but more prolonged decline. GDP growth hovered around 0.5 percentage points below the mean in the early quarters. Inventory intensity also declined, with a delay of one quarter, and remained depressed for several periods. The parallel movements of both lines suggest a persistent and gradual adjustment. In contrast, the COVID recession of 2020 shows a very different pattern. GDP growth plummeted in Q0 (-2.2 p.p.) and Q+1 (−10.3 p.p.), but then rebounded sharply at Q+2, peaking at +7.7 p.p. above the mean. In contrast to the typically strong pro-cyclical inventory behaviour, inventory investment remained relatively stable during this recession, indicating a decoupling from the usual pattern. A modest destocking episode occurred from Q+1 to Q+3. Instead of significantly amplifying the downturn, inventories rather acted as a stabilizer this time. Notably, a phase of very strong inventory accumulation began two quarters after the GDP rebound. This strong restocking likely reflects firms' efforts to enhance resilience amid supply chain uncertainty, turning inventory investment into a key driver of the recovery starting in 2020.

4. Conclusion

This paper has examined the complex and potentially evolving role of inventories in shaping macroeconomic fluctuations across 29 European countries over the period 1999–2023, thereby covering three major recessions. By combining descriptive analysis with dynamic panel-econometric techniques that distinguish between short-run and long-run inventory behaviour, we disentangle the intricate interplay of demand and supply signals. The use of different statistical methods in conjunction allows us to uncover robust stylized facts and identify emerging patterns.

Our findings confirm the broadly pro-cyclical nature of inventories, but also reveal a more nuanced cyclical dynamic than is typically assumed. In response to an increase in aggregate sales, inventories are initially depleted, before a pro-cyclical restocking pattern emerges. Notably, some models indicate a systematic correction in inventory levels starting around four quarters after the initial shock. These phase shifts underscore the importance of distinguishing between short- and long-run inventory behavior to avoid empirical pitfalls in assessing their macroeconomic role.

With respect to recessions, inventory responses show significant time lags, with depletions typically occurring one to three quarters after a GDP decline has begun—reflecting adjustment frictions in production and supply chains. These adjustment paths differ substantially across countries and recessions. During the Great Recession and the Eurozone crisis, inventories amplified GDP contractions, accounting for up to 60–80% of total output losses on average. In contrast, the COVID-19 recession marked a fundamental break from this pattern: inventory drawdowns were limited, and restocking occurred earlier and more abruptly. The average ratio of inventory depletion to GDP loss fell to just 33%, pointing to a possible structural shift in corporate stocking strategies—likely driven by heightened uncertainty and global supply chain disruptions.

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