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Does Inventory Management Improve Profitability? Empirical Evidence from Polish Manufacturing Industries

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Abstract:

Purpose: The main purpose of this article is to investigate the relationship between inventory management and industrial processing companies' financial performance. In analyzing these relationships, the study took account of total inventories (INV) and their components, i.e., materials and raw materials (RMI), intermediates and work-in-progress (WIP), finished products (FGI), and commodities (GI).

Approach/Methodology/Design: Descriptive statistics and dynamic panel regression were used in analyzing the causative links between the efficiency of inventory management and profitability. The analysis was carried out on a 2013–2019 database for the Polish industrial processing sector, taking into account the size classes of enterprises.

Findings: The article proves the existence of statistically significant relationships between the efficiency of total inventories and inventory components (except for finished products), on one side, and business profitability, on the other. The estimated panel regression parameters showed that the days in inventory ratios for intermediates and work-in-progress (WIPC) and raw and other materials (RMI) have the strongest correlation with profitability. Increasing the inventory days for these components had the strongest and negative impact on the return on total assets in the population surveyed and in enterprise size classes identified in this study.

Practical implications: The study provides evidence for financial benefits derived from inventory performance. Also, it indicates which inventory components have the greatest impact on financial results.

Originality/value: The article extends knowledge on causative links between the management of inventories and inventory components and enterprises' financial performance. It also analyzes the results of inventory management by industrial processing sub-sector and by enterprise size. The results confirm that it is advisable to adjust the volume and mix of inventories because rational inventory management practices are also a factor that empowers industrial company owners to add more value.

Keywords: Profitability, inventory management, manufacturing industry, panel data analysis, Poland.

JEL classification: G31, L25, L60.

Paper Type: Research study.

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1. Introduction

Inventory management is among the key areas of operational management. Indeed, if implemented, it is a management function that allows both to sufficiently address the demand and avoid production surpluses or deficiencies through permanent monitoring and forecasting of inventory levels. However, the topics related to inventory management efficiency extend over more than just demand and logistic aspects. This is because the financial aspect of inventory management, related to the need for keeping stocks and to the costs they generate, is a matter of extreme importance (Gołaś and Bieniasz, 2016).

The companies keep stocks for several reasons, which differ depending on inventory types' particularities (Kempny, 1995; Kisperska-Moroń, 1995; Kolias *et al.*, 2011). As regards stocks of raw and other materials, the main reason is the commitment to ensure cyclical production processes; potential economies of scale in production and distribution; the reduction of risks involved in the uncertainty of delivery quantities and times; and the reduction of impacts of seasonality in supply and demand. The fundamental reason for keeping sufficient stocks of finished products is the need to ensure continuous sales; otherwise, sales profits could go down, and the company would lose its reputation, which would have a deteriorating effect on its competitive position. However, stocks entail various types of costs involved in stock keeping and ordering processes. This primarily includes warehousing, handling, transport costs, insurance, losses of goods held in stocks, loss of volume discounts on orders, costs of running out of stocks, and lost profits resulting from the tying-up of capital in stocks.

Effective inventory management is critical also because of the considerable share of stocks in the assets structure. In most companies, except for the financial and service sector, stocks make up a major part of both current and total assets. A characteristic example is retail trade companies where these ratios reach the highest levels (Gaur *et al.*, 2005; Kolias *et al.*, 2011). According to the European Central Bank (ECB), stocks also account for a considerable part of assets held by industrial companies (Bank for..., 2020). For instance, according to recent (2018) data published by the ECB, in selected EU countries, the share of stocks in total assets and current assets of industrial processing companies was as follows, respectively (Bank for..., 2020): 9–12% and 22–27% (Belgium, Germany), 15–17% and 28–35% (Croatia, Spain, Portugal, France, Italy, Czech Republic, Slovakia, Poland) and 23% and 39% (Austria).

Therefore, this paper aims to verify the causative link between the efficiency of inventory management and the financial performance of industrial processing companies. So far, such research has been carried out to a limited extent and has usually failed to consider the internal mix of inventories. This paper presents the findings from a case study of industrial processing sub-sectors in Poland and is structured as follows: the introduction is followed by a synthetic literature review, with the focus being mostly on methodological aspects and the results of empirical studies on the impacts of inventory management efficiency on the financial

performance of businesses. The next subchapter formulates the research hypotheses, presents information on source materials, and describes its methods. The following part of this paper shows the characteristics of inventory management in the Polish industrial processing sector. It discusses the changes in stocks' share in assets and changes in the internal mix of inventories. Also, it includes a comparative analysis of the duration of inventory cycles grouped by company size and by industrial processing sub-sector. Next, it presents the results of the estimation of regression models used to determine how strong and how oriented the impact of the duration of inventory cycles on profitability. The last part of this paper includes the conclusions.

2. Literature Review

The literature on the subject can be observed to include a series of papers that analyze the impact of inventory management on companies' financial performance. These issues were often analyzed in the context of working capital efficiency; in addition to examining the impacts of short-term receivables and liabilities, the authors also dove into the effects of inventory management on financial performance. Generally, a vast majority of research (e.g., Deloof, 2003; Dong and Su, 2010; Lazaridis and Tryfonidis, 2006; Padachi, 2006; Raheman *et al.*, 2010; Ramachandran and Janakiraman, 2009; Gołaś, 2020) suggest that increasing the days in inventory has an adverse effect on the financial performance of businesses, measured with different categories of profitability ratios.

Financial benefits driven by a reduction in inventory ratio days are also identified in a series of studies carried out at the sector, sub-sector, and industrial company levels. This primarily includes research which validates the impact of improvements in stock management on the financial performance of industrial companies measured with the return on sales (Capkun *et al.*, 2009; Eroglu and Hofer, 2011; Koumanakos, 2008; Roumiantsev and Netessine, 2007; Shah and Shin, 2007; Gołaś and Bieniasz, 2016), the return on capital employed (Cannon, 2008; Obermaier and Donhauser, 2009), the return on assets (Cannon, 2008; Gołaś and Bieniasz, 2016; Gołaś, 2020), and the long-term rate of return on shares (Chan *et al.*, 2005).

However, when analyzing the relationship between stocks' productivity and financial performance, the researchers usually took aggregated inventories into account while failing to address their components (mix). Generally, there is a dearth of studies that take discrete inventory types into account in the literature (e.g., Capkun *et al.*, 2009; Ganas and Hyz 2015; Balakrishnan *et al.*, 1996; Boute *et al.*, 2007; Eroglu and Hofer, 2011; Isaksson and Seifert, 2014; Lieberman *et al.*, 1999, Gaur and Bhattacharya, 2011; Manikas, 2017; Bendig, 2018; Shin *et al.*, 2016). Hence, there is only a little knowledge of the impacts of discrete inventory types on corporate financial performance. This paper intends to close that gap and presents the findings from research carried out in the Polish industrial processing sector, taking four main discrete inventory types into account, i.e., raw and other materials; intermediate products and work-in-progress; finished products; and commodities.

3. Research Hypotheses, Source Materials and Methodological Aspects

The literature review presented above suggests that a significant and generally positive relationship exists between stock management efficiency (measured with the Days Sales of Inventory) and financial performance at the company level. This provides grounds for formulating the following hypotheses:

H1: the days in inventory ratio for total stocks differ between periods, company size classes, and industrial processing sub-sectors;

H2: the days in inventory ratio for discrete inventory types (materials; intermediate products and work-in-progress; finished products; commodities) differs between periods, company size classes, and industrial processing sub-sectors;

H3: a positive/negative correlation exists between reducing/increasing the days in inventory ratio for total stocks and financial performance of industrial processing companies;

H4: a positive/negative correlation exists between reducing/increasing the days in inventory ratio for discrete inventory types (materials; intermediate products and work-in-progress; finished products; commodities) and financial performance of industrial processing companies.

The verification of hypotheses H1 to H4 and the analysis of the inventory–performance relationship relied on unpublished data of the Polish Central Statistical Office (Financial..., 2013–2019) regarding the financial condition of the industrial processing sector and its sub-sectors (NACE C10–C33, 2-digit numerical code) identified as per the Statistical Classification of Economic Activities in the European Community (NACE 2008). The study was conducted with a panel of 24 industrial processing sub-sectors. Data from 2013–2019 was collected for three company size classes (small, medium, large). These data sources were used as a basis for determining the parameters of panel regression models, which included the days in inventory for total stocks ($INVTC_{j,t}$) and the corresponding sub-indexes for stocks of raw and other materials ($RMIC_{j,t}$), stocks of intermediate products and work-in-progress ($WIPC_{j,t}$), stocks of finished products ($FIGC_{j,t}$), and stocks of commodities ($GIC_{j,t}$). The indexes were calculated as follows:

$$RMIC_{j,t} = \frac{\text{average level } (RMI_{j,t_b}, RMI_{j,t_e}) \times 365}{\text{costs of energy and materials consumption}} \quad (1)$$

$$WIPC_{j,t} = \frac{\text{average level } (WIP_{j,t_b}, WIP_{j,t_e}) \times 365}{\text{cost of goods sold}} \quad (2)$$

$$FIGIC_{j,t} = \frac{\text{average level } (FGI_{j,t_b}, FGI_{j,t_e}) \times 365}{\text{cost of goods sold}} \quad (3)$$

$$GIC_{j,t} = \frac{\text{average level } (GI_{j,t_b}, GI_{j,t_e}) \times 365}{\text{value of commodities and materials sold}} \quad (4)$$

$$INVTC_{j,t} = RMIC_{j,t} + WIPC_{j,t} + FGIC_{j,t} + GIC_{j,t} \quad (5)$$

where: $RMIC_{j,t_{b,e}}$, $WPI_{j,t_{b,e}}$, $FGI_{j,t_{b,e}}$, $FGI_{j,t_{b,e}}$ is the value of discrete inventory components in sub-sector j at the beginning (t_b) and end (t_e) of year t .

In turn, the return on assets ($ROA_{j,t}$) is the metric used in assessing the financial efficiency of industrial processing sub-sectors, and is calculated as follows:

$$ROA_{j,t} = \frac{EBIT_{j,t} \times 100}{\text{average level}(TA_{j,t_b}, TA_{j,t_e})} \quad (6)$$

where: $EBIT_{j,t}$ - operating profit, $TA_{j,t_{b,e}}$ - total assets.

The panel data methodology was used in assessing the impact of inventory management on financial performance, i.e., in verifying the research hypotheses. It avoids the endogeneity problem, and the issues related to measurement errors and time series are not long enough. Also, employing these methods is a way to control and eliminate heterogeneity (Hsiao, 1985). The parameters of ROA models were estimated using the two-step dynamic system estimator of the Generalized Methods of Moments (GMM), developed by Blundell and Bond (1998), with a robust variance estimator (Windmeijer, 2005). The dynamic panel models developed on that basis were assessed with the Arellano–Bond test (AR-2) and the Hansen test. This provided grounds for verifying the hypothesis of autocorrelation in the random effect, which assumes the absence of autocorrelation in second-order random effect, and for checking whether it is justified to introduce additional elements. The null hypothesis is the absence of correlation between instrumental variables and the random effect (Arellano and Bond 1991; Blundell and Bond 1998). The calculations were based on the xtabond2 estimator available in the STATA 15 statistical suite.

The parameters of regression models shown below were used in testing the research hypotheses $H1$ – $H4$ regarding the impact of inventory management on the financial performance of industrial processing sub-sectors:

$$ROA_{j,t} = a_0 + b_1 ROA_{j,t-1} + b_2 RMIC_{j,t} + \sum_{k=1}^K b_k X_{k,j,t} + (\alpha_j + \varepsilon_{jt}) \quad (7)$$

$$ROA_{j,t} = a_0 + b_1 ROA_{j,t-1} + b_2 WIPC_{j,t} + \sum_{k=1}^K b_k X_{k,j,t} + (\alpha_j + \varepsilon_{jt}) \quad (8)$$

$$ROA_{j,t} = a_0 + b_1 ROA_{j,t-1} + b_2 FGIC_{j,t} + \sum_{k=1}^K b_k X_{k,j,t} + (\alpha_j + \varepsilon_{jt}) \quad (9)$$

$$ROA_{j,t} = a_0 + b_1 ROA_{j,t-1} + b_2 GIC_{j,t} + \sum_{k=1}^K b_k X_{k,j,t} + (\alpha_j + \varepsilon_{jt}) \quad (10)$$

$$ROA_{j,t} = a_0 + b_1 ROA_{j,t-1} + b_2 INVCT_{j,t} + \sum_{k=1}^K b_k X_{k,j,t} + (\alpha_j + \varepsilon_{jt}) \quad (11)$$

where: a_0 - constant of equation, $ROA_{j,t-1}$ - return on assets in year $t - 1$, $RMIC_{j,t}$, $WIPC_{j,t}$, $FGIC_{j,t}$, $GIC_{j,t}$, $INVCT_{j,t}$ - inventory cycles, $X_{k,j,t}$ - set of control variables, ε - random effect, α_j - group effect (constant over time).

The control variables were selected based on other studies carried out to econometrically analyze the inventory–performance relationship. Usually, these studies used different metrics of company size, assets structure, capital intensity, liquidity, leverage and income growth ratios as control variables (e.g. Capkun *et al.*, 2009; Eroglu and Hofer, 2011; Ganas and Hyz, 2015; Alrjoub and Ahmad, 2017). Four control variables (in addition to inventory cycles) were used to build the models:

$ROS_{j,t}$: return on sales $\left(\frac{EBIT \times 100}{Sales}\right)$, $QR_{j,t}$: liquidity ratio $\left(\frac{Current\ assets - inventory}{short-term\ liabilities}\right)$,

$lnTA_{j,t}$: logarithmized value of total assets (per company), $SFA_{j,t}$: share of fixed

assets in total assets $\left(\frac{Fixed\ assets \times 100}{Total\ assets}\right)$, $\Delta S_{j,t}$: growth rate of sales proceeds

$\left(\frac{(S_t - S_{t-1}) \times 100}{S_{t-1}}\right)$, $ICEQ_{j,t}$: capital leverage ratio $\left(\frac{Invested\ capital}{Equity}\right)$.

4. Results and Discussion

4.1 Importance of Inventory and Inventory Performance in the Polish Manufacturing industry

Table 1 presents the basic characteristics of inventories prevailing in the Polish industrial processing sector. These are aggregated figures for 2013–2019. The analysis suggests the share of inventories in total assets and in current assets remained at a similar level throughout this period while following a moderate yet noticeable growth trend ($\Delta_{RC}=0.58\%$ and $\Delta_{RC}=0.72\%$). As a consequence, the share of inventories in total assets grew from 15.1–15.4% (2013–2014) to 15.9–16.4% (2018–2019) and the share of inventories in current assets went up from 33.2–32.4% (2013–2014) to 34.7–35.2% (2018–2019).

The data also implies that the study period witnessed moderate though noticeable changes in the inventory mix. The growth ratio used in this study (Δ_{RC}) suggests that the share of raw and other materials (RMI) and intermediate products and work-in-progress (WIP) followed a weak growth trend while the share of finished products (FGI) and commodities (GI) declined at a clearly faster rate. However, these changes did not essentially affect the inventory mix. Both at the beginning and the end of the study period, raw and other materials (RMI) and finished products (FGI) remained the key components of the inventory mix in the Polish industrial processing sector, making up 45.6% and 47.5% (RMI) and 28.8% and 26.2% (FGI), respectively, of the total inventory value.

This means these categories consistently play a major role in inventory management in the industrial processing sector. The great importance of managing these very categories of inventories is also corroborated by the analysis of inventory cycles,

which suggests that in the study period, the days in inventory ratio for raw and other materials (RMIC) and finished products (FGIC) was largely determinant (up to 55–58%) for the day's sales in inventory for total stocks (INVTC).

Moreover, data in Table 1 suggests that the days in inventory for total stocks were quite largely determined by the days in inventory ratio for commodities (GIC) throughout the study period. Although commodities had a relatively small share (7–8%) in total inventory value, their replacement cycle was relatively long (25–33 days) and was also a relatively strong determinant (33–35%) of days in inventory for total stocks nearly throughout the 2013–2019 period.

In turn, considering the target and pace of changes in the duration of inventory sub-cycles (Table 1, Figure 1), it needs to be emphasized that the industrial processing sector witnessed an increase both in the days in inventory ratio for total stocks and most sub-indexes for discrete inventory components.

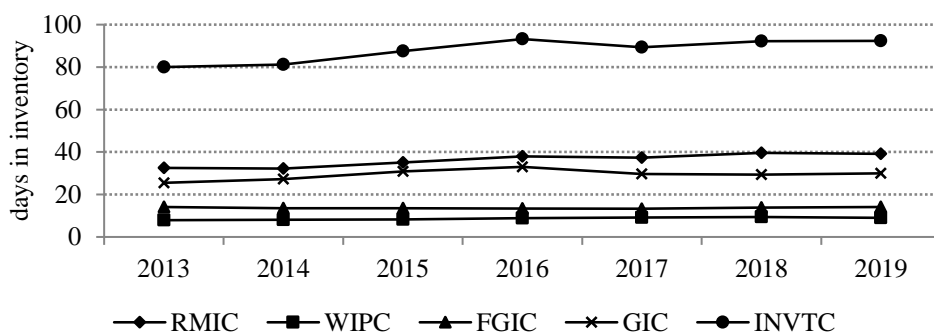
The adverse trend followed by the days in inventory ratio for total stocks (INVTC, $\Delta_{RC}=2.42\%$) in 2013–2019 was driven to a similar extent by the increase in the days in inventory ratio for raw and other materials (RMIC, $\Delta_{RC}=3.14\%$), commodities (GIC, $\Delta_{RC}=2.78\%$) and intermediate products and work-in-progress (WIPC, $\Delta_{RC}=2.22\%$). Against this background, the days in inventory ratio for finished products changed only slightly. Indeed, the corresponding inventory cycle (FGIC) did not undergo any major changes in 2013–2017 (13.4–14.1 days, $V=2.4\%$, $\Delta_{RC}=0.02\%$) and therefore had a marginal impact on the changes in days in inventory for total stocks (INVTC).

Table 1. Basic inventory characteristics in the Polish manufacturing industry in 2013–2019 (average value, total NACE C).

Specification ¹	2013	2014	2015	2016	2017	2018	2019	V ²	Δ_{RC} ³
Share in total inventory (%):									
Total assets	15.4	15.1	15.2	15.2	15.6	16.4	15.9	3.1	0.58
Current assets	33.2	32.4	32.6	32.4	32.9	35.2	34.7	3.4	0.72
Inventory mix (%):									
RMI	45.6	44.1	45.7	47.5	47.4	48.1	47.5	3.1	0.69
WIP	16.2	16.5	16.1	16.9	17.5	17.1	16.8	3.0	0.59
FGI	28.8	27.6	26.4	25.6	25.6	25.3	26.2	4.9	-1.58
GI	8.0	8.3	8.1	8.2	7.7	7.3	7.4	5.2	-1.17
Days in inventory:									
RMIC	32.5	32.2	35.1	38.0	37.3	39.6	39.2	8.4	3.14
WIPC	7.9	8.1	8.2	8.9	9.1	9.4	9.0	6.6	2.22
FGIC	14.1	13.6	13.5	13.4	13.3	13.8	14.1	2.4	0.02
GIC	25.5	27.2	30.9	33.0	29.6	29.3	30.0	8.3	2.78
INVTC	80.0	81.2	87.6	93.2	89.4	92.2	92.3	6.1	2.42

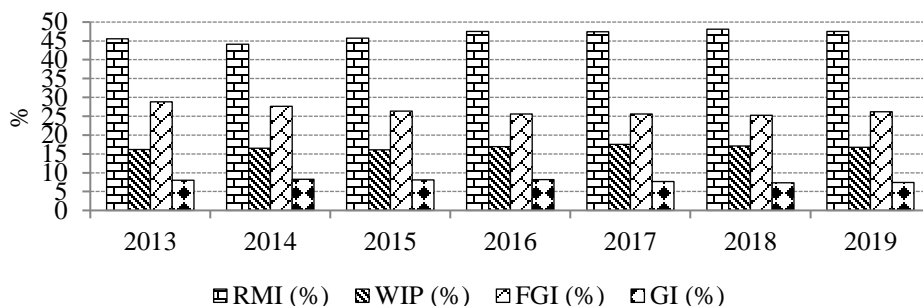
¹RMI: share of raw and other materials in inventories (%); WIP: share of intermediate products and work-in-progress in inventories (%); FGI: share of finished products in inventories (%); GI: share of commodities in inventories (%); RMIC: days in inventory ratio for raw and other materials; WIPC: days in inventory ratio for intermediate products and work-in-progress; FGIC: days in inventory ratio for finished products; GIC: days in inventory ratio for commodities; INVTIC: days in inventory ratio for total stocks; ²V: coefficient of variation (%); ³ Δ_{RC} : average annual growth rate (%) (geometric mean).
Source: Own calculation based on Financial.... (2013-2019).

Figure 1. Changes in days in inventory ratios in the Polish manufacturing industry over time.



Source: Own compilation based on Table 1.

Figure 2. Changes in the inventory mix in the Polish manufacturing industry over time.



Source: Own compilation based on Table 1.

The changes in the inventory mix at the general level of industrial processing, as presented above, and the management efficiency of these assets measured with the respective days in inventory ratios, reveal a series of differences between company size groups (Table 2). The share of inventories in total assets (15.7–17%) and current assets (28.7–30.6%) was relatively smaller in the small enterprise sector and followed a moderate yet noticeable downward trend. In turn, when it comes to medium and large enterprises, the corresponding shares were higher and followed an upward trend in the study period. The differences in the levels of, and trends followed by, ratios

covered by this study are also noticeable in the inventory mix. The small enterprise sector saw an increase in the share of intermediate products and work-in-progress (WIP), whereas the share of finished products (FGI) and commodities (GI) declined at a similar rate. In turn, as regards medium enterprises, the inventory mix was quite stable in the study period, as reflected by the relatively small growth rates for discrete inventory types. However, what makes large industrial processing companies stand apart is a relatively stronger decline in the share of finished products in total inventories. Indeed, in that group of enterprises, the changes in the share of this type of inventories (FGI) in total stocks occurred the fastest ($\Delta_{RC}=-2,16\%$). Consequently, their share declined from 30% to 26% over the study period, which is the greatest drop of all company size classes covered by this analysis.

Data from Table 2 also reveal several differences in inventory management efficiency (measured with the days in inventory ratio) and in the trends followed by the changes. Generally, between 2013 and 2019, all three size classes of industrial processing companies witnessed an increase in the days in inventory ratio for total stocks (INVTC); this suggests a deterioration in how these assets are managed. That adverse trend is most noticeable in large enterprises ($\Delta_{RC}=2.77\%$); although their days in inventory ratio for total stocks (INVTC) was the shortest in all years, it went up from 73 days (2013–2014) to nearly 86 (2019), i.e., by more than 17%. Nevertheless, it does not change how company size class compares to small and medium enterprises; in their case, inventory management efficiency, measured with the days in inventory ratio for total stocks (INVTC), was 25–30% higher in the years covered by this study. In turn, considering the sub-cycles, it can be noticed that the days in inventory ratios for raw and other materials (RMIC) and commodities (GIC) were decisive for the days in inventory ratios for total stocks; the above is true for all company size classes. Moreover, these ratios' adverse trend (due to them becoming longer) was the strongest determinant of unfavorable changes in the days in inventory ratio for total stocks in all of the large, medium, and small industrial processing companies.

Table 3 presents the basic characteristics of inventories grouped by industrial processing sub-sectors. Based on the example of 2019 data, it can be concluded that the differences between these characteristics are greater than when grouped by company size. As regards the coefficient of variation (V), it can be noticed that the greatest differences between industrial processing sub-sectors exist in the days in inventory ratio for intermediates and work-in-progress (WIPC, $V=100\%$) and in the share of that discrete inventory type in total stocks (WIP, $V=59.2\%$). The days in inventory ratio for this type of inventory is particularly long (WIPC=56.7 days) in the manufacture of other transport equipment (C30), which is also where they have the greatest share in total stocks (WIP=45.8%). In turn, the fastest rotation of intermediates and work-in-progress, i.e., the shortest days in inventory (WIPC=1.2 days), was reported in the manufacture of tobacco products (C12), a sub-sector where that discrete inventory type is of marginal importance as it accounts for only 1.2% of total inventory value.

Table 2. Basic inventory characteristics in the Polish manufacturing industry in 2013–2019, grouped by enterprise size (average value, total NACE C).

Specification ¹		2013	2014	2015	2016	2017	2018	2019	V ²	ΔRC ³
Small enterprises (10–49 employees)										
Inventories to total assets	%	16.4	17.0	16.5	15.9	16.5	16.0	15.7	2.79	-0.75
Inventories to current assets		30.2	30.6	30.2	29.1	30.4	29.5	28.7	2.39	-0.87
RMI		45.8	43.3	44.6	47.8	46.8	49.1	48.4	4.57	0.93
WIP		11.7	12.3	11.5	11.7	12.9	12.7	12.9	5.08	1.70
FGI		21.7	20.5	20.2	20.1	20.5	19.8	20.1	3.03	-1.26
GI		17.3	18.8	18.0	18.4	16.9	15.6	15.4	7.75	-1.98
RMIC	days	37.9	39.0	40.7	45.2	45.6	47.8	46.0	9.04	3.28
WIPC		6.3	7.0	6.6	6.8	7.8	7.6	7.4	7.74	2.78
FGIC		11.6	11.6	11.5	11.7	12.3	11.8	11.5	2.37	-0.21
GIC		45.8	47.8	52.9	52.5	53.7	52.1	49.5	5.90	1.29
INVTC		101.6	105.3	111.8	116.2	119.4	119.2	114.3	6.09	1.99
Medium-sized enterprises (50–249 employees)										
Inventories to total assets	%	16.7	16.5	16.9	16.6	16.9	17.9	17.1	2.89	0.38
Inventories to current assets		33.5	33.5	33.7	33.3	34.0	35.4	34.7	2.25	0.61
RMI		44.6	44.1	43.6	45.5	46.7	46.4	46.2	2.73	0.56
WIP		16.7	16.0	15.3	16.1	16.0	16.1	15.8	2.54	-0.91
FGI		27.8	27.8	27.5	28.0	27.2	26.9	27.5	1.37	-0.17
GI		8.8	8.9	8.7	9.1	8.2	7.9	8.5	4.70	-0.56
RMIC	days	35.0	35.8	37.8	40.3	40.9	42.7	41.2	7.54	2.78
WIPC		8.8	8.6	8.7	9.1	9.1	9.6	9.1	4.01	0.56
FGIC		14.6	14.9	15.6	15.8	15.5	16.1	15.7	3.51	1.31
GIC		43.2	42.6	44.4	45.5	42.9	44.3	49.1	5.02	2.15
INVTC		101.5	101.9	106.5	110.8	108.4	112.8	115.1	4.83	2.12
Large enterprises (250 or more employees)										
Inventories to total assets	%	14.8	14.5	14.5	14.6	15.1	16.0	15.6	3.85	0.84
Inventories to current assets		33.4	32.2	32.5	32.5	32.8	35.7	35.2	4.28	0.87
RMI		45.9	44.2	46.6	48.1	47.7	48.6	47.8	3.28	0.69
WIP		16.5	17.1	16.9	17.8	18.5	17.8	17.4	3.85	0.87
FGI		30.0	28.4	26.7	25.3	25.5	25.2	26.3	6.69	-2.16
GI		6.7	6.9	6.8	6.9	6.6	6.4	6.5	3.12	-0.53
RMIC	days	31.3	30.5	33.7	36.6	35.6	38.2	38.1	8.96	3.36
WIPC		7.8	8.1	8.2	9.0	9.3	9.4	9.2	7.45	2.68
FGIC		14.2	13.4	13.0	12.8	12.8	13.3	13.9	4.08	-0.41
GIC		19.3	20.8	24.3	26.7	23.6	23.8	24.4	10.50	3.96
INVTC		72.6	72.8	79.2	85.0	81.3	84.7	85.6	6.96	2.77

¹Designations as in table 1; ²V: coefficient of variation (%); ³ Δ_{RC} : average annual growth rate (%) (geometric mean).

Source: Own calculation based on: *Financial... (2013–2019)*.

Table 3. Basic inventory characteristics in the Polish manufacturing industry in 2019, grouped by manufacturing industry sub-sector (average value, total NACE C10–C33).

NACE C10– C33 ¹	Share of inventories in:		Inventory mix ² :				Days in inventory ² :				
	Total assets	Current assets	RMI	WIP	FGI	GI	RMIC	WIPC	FGIC	GIC	INVTC
	%		%				days				
C10	15.0	33.4	39.5	13.0	38.1	8.0	22.1	5.5	16.0	24.7	68.2
C11	8.9	22.0	42.5	7.9	31.6	11.8	36.6	2.3	9.0	61.0	108.9
C12	18.6	64.9	79.9	2.4	14.9	1.3	141.2	1.2	7.6	5.9	156.0
C13	22.5	42.0	46.2	12.1	30.9	8.4	50.3	8.4	21.3	79.1	159.1
C14	28.6	44.0	41.3	11.2	33.7	12.0	109.5	10.6	32.0	85.0	237.2
C15	25.1	38.6	36.8	19.9	34.9	7.9	63.3	18.1	31.9	90.9	204.2
C16	13.4	41.4	46.2	13.9	33.9	5.0	43.6	8.2	20.2	29.2	101.3
C17	11.1	29.5	49.7	8.7	36.0	5.2	29.7	3.6	14.8	44.0	92.0
C18	10.0	22.0	51.6	15.9	22.3	8.4	36.1	5.5	7.7	52.0	101.2
C19	18.3	44.8	60.0	7.7	26.2	6.0	49.3	4.3	14.6	6.8	75.0
C20	12.5	32.6	48.3	9.6	30.3	10.7	36.5	5.0	15.9	65.4	122.8
C21	12.4	28.8	40.1	13.6	25.7	19.6	93.9	13.1	24.7	79.9	211.6
C22	15.4	33.7	46.0	12.1	32.0	8.6	37.9	6.4	16.8	56.6	117.7
C23	13.4	34.3	38.7	9.4	42.1	8.5	46.4	6.1	27.3	55.0	134.7
C24	19.2	44.5	45.1	27.0	25.7	1.6	40.7	17.8	16.9	15.6	91.0
C25	17.7	36.0	48.6	21.2	18.1	7.5	56.0	14.0	11.9	44.6	126.6
C26	19.7	28.1	60.0	14.7	17.8	5.2	37.4	7.1	8.6	45.7	98.8
C27	18.9	37.7	52.3	12.3	24.7	9.8	48.3	8.3	16.6	40.4	113.6
C28	19.9	33.9	43.8	29.6	18.1	5.5	62.7	24.0	14.7	44.0	145.4
C29	12.8	27.7	53.4	18.7	18.3	8.3	25.2	6.4	6.3	41.3	79.3
C30	25.4	42.1	36.5	45.8	5.4	1.5	74.3	56.7	6.7	60.7	198.4
C31	16.3	37.2	47.5	12.0	32.6	6.4	36.4	5.6	15.1	37.5	94.6
C32	23.3	45.3	37.7	17.6	23.1	19.8	68.2	17.1	22.4	105.9	213.7
C33	12.3	19.7	47.8	34.0	3.6	10.2	69.7	15.1	1.6	37.3	123.6
V ³	30.7	26.9	19.9	59.2	37.7	55.9	50.9	100.0	50.1	50.7	36.7
Min. ⁴	8.9	19.7	36.5	2.4	3.6	1.3	22.1	1.2	1.6	5.9	68.2
Max. ⁵	28.6	64.9	79.9	45.8	42.1	19.8	141.2	56.7	32	105.9	237.2
Med. ⁶	17	35.1	46.2	13.3	25.9	8.1	47.3	7.6	15.5	45.1	120.2

¹Manufacturing industry sub-sector codes: C10: Manufacture of food products; C11: Manufacture of beverages; C12: Manufacture of tobacco products; C13: Manufacture of textiles; C14: Manufacture of wearing apparel; C15: Manufacture of leather and related products; C16: Manufacture of wood, cork, straw and wicker; C17: Manufacture of paper and paper products; C18: Printing and reproduction of recorded media; C19: Manufacture of coke and refined petroleum products; C20: Manufacture of chemicals and chemical products; C21: Manufacture of pharmaceutical products; C22: Manufacture of rubber and plastic products; C23: Manufacture of other non-metallic mineral products; C24: Manufacture of basic metals; C25: Manufacture of metal products; C26: Manufacture of computer, electronic and optical products; C27: Manufacture of electrical equipment; C28: Manufacture of machinery and equipment n.e.c.; C29: Manufacture of motor vehicles, trailers and semi-trailers; C30: Manufacture of other transport equipment; C31: Manufacture of furniture; C32: Other manufacturing; C33: Repair and installation of machinery and equipment.

²Designations as in Table 1; ³V: Coefficient of variation (%); ⁴Min: minimum value; ⁵Max: maximum value; ⁶Med: median.

Source: Own calculation based on: *Financial...*, (2013–2019).

4.2 Relationship between Inventory Cycles and Profitability: a Dynamic Panel Analysis

Because of the generally favorable trends followed by inventory performance figures, as shown in the previous part of this paper, it is somehow natural to ask the nature and strength of relationships between these ratios and financial performance. These relationships were examined using the panel survey methodology and Polish industrial processing sub-sectors' parameters at the section level (2-digit code level) (NACE, 2008). Some data is missing due to national regulations on statistical secrecy in research. Hence, depending on the grouping criterion, data was retrieved for 23 sub-sectors (in the group of small, medium, and large enterprises) or 69 sub-sectors (in the total industrial processing sector). The parameters of dynamic panel regression models were estimated for the total industrial processing sector and separately for three company size classes. The estimation was preceded by an analysis of the correlation between variables used in the models.

Considering the descriptive statistics of variables covered by the analysis (Table 4), it can be noted that inventory management figures (measured as days in inventory) vary strongly across the population surveyed. Indeed, variation is quite pronounced, especially when it comes to days in inventory for intermediate products and work-in-progress (WIPC, $V=89.9\%$) and, to a lesser degree, for finished products (FGIC, $V=51.8\%$) and commodities ($V=60.8\%$). Moreover, $\bar{x} > \text{Med}$ for each type of inventory cycle; reflects a minor left-side asymmetry in the distribution of observations, which means that cases with an above-average day in inventory ratio predominate. In turn, much smaller differences were recorded in the vast majority of other variables, except for ΔS and ICEQ. Indeed, as regards the growth rate of sales proceeds (ΔS) and the capital leverage ratio (ICEQ), the differences are extremely high, too (424.1% and 87.9%).

Table 4. Descriptive statistics^{1,2}

Statistics	ROA	ROS	QR	SFA	ICEQ	lnTA	ΔS	RMIC	WIPC	FGIC	GIC	INVTVC
\bar{x}	8.5	7.0	1.1	48.3	1.9	8.8	3.5	50.5	10.3	15.0	54.4	130.3
Min	-2.8	-1.2	0.4	21.9	1.2	5.5	-50.1	10.0	0.0	0.8	0.9	24.2
Max	18.6	20.5	2.1	72.9	35.9	13.6	153.5	131.3	73.6	47.4	232.2	339.6
Med	8.4	6.9	1.1	48.2	1.7	8.6	2.9	44.9	7.8	14.5	48.8	118.5
V	33.9	36.6	22.1	21.3	87.9	17.5	424.1	44.0	89.9	51.8	60.8	41.6

¹The statistics were calculated based on 404 observations from the sector of small (134 observations), medium (134 observations) and large (136 observations) enterprises. ² \bar{x} : mean, Min: minimum, Max: maximum, V: coefficient of variation (%), Med: median.

Source: Own calculations.

Table 5 presents the Pearson's linear correlation coefficients for all the variables under consideration and building the regression models. The analysis suggests a negative relationship exists between the return on assets (ROA) and days in inventory for all inventory types. However, the relationship is not statistically significant in the case of

days in inventory for intermediates and work-in-progress (WIPC) and for finished products (FGIC). Also, what is largely obvious, data in Table 5 suggests that a positive relationship exists between the return on assets and return on sales (ROS). In contrast, a negative relationship exists between that category of profitability and liquidity (QR), assets structure (SFA), and company size (lnTA).

Table 5. Correlation matrix (Pearson's correlation coefficients)¹.

	ROA	ROS	QR	SFA	ICEQ	lnTA	ΔS	RMIC	WIPC	FGIC	GIC	INVTG
ROA	1.000											
ROS	0.807*	1.000										
QR	-0.423*	-0.447*	1.000									
SFA	-0.282*	-0.024	-0.383*	1.000								
ICEQ	-0.045	-0.014	-0.268*	-0.041	1.000							
lnTA	-0.208*	-0.126*	-0.230*	0.439*	-0.112*	1.000						
ΔS	0.023	0.068	-0.036	-0.013	-0.029	0.078	1.000					
RMIC	-0.108*	-0.181*	0.154*	-0.413*	-0.029	-0.449	-0.102*	1.000				
WIPC	-0.075	-0.038	0.012	-0.233*	-0.071	-0.008	0.009	0.412*	1.000			
FGIC	-0.023	-0.056	-0.036	0.048	-0.072	-0.152*	-0.051	0.367*	0.019	1.000		
GIC	-0.181*	-0.139*	0.185*	-0.277*	-0.056	-0.367	-0.089*	0.423*	0.163*	0.354*	1.000	
INVTG	-0.145*	-0.167*	0.174*	-0.371*	-0.069	-0.413*	-0.102*	0.791*	0.442*	0.513*	0.862*	1.000

¹Significance levels: * $p \leq 0.05$.

Source: Own calculations.

Table 6 presents the regression parameters for five-panel regression models of the return on assets of industrial processing companies (at the general level) together with appropriate tests and statistics. The second-order autocorrelation (AR-2) test results presented in the Table show that moment conditions used in the estimation process are correct ($p=0.136$ – 0.286). The validity of all models is corroborated by Hansen's J-test, according to which correlation ($p=0.786$ – 0.942) between instrumental variables and the random effect does not exist in any of the models.

The analysis of parameters of regression models (Table 6) suggests that all inventory cycles used in this study prove to be statistically significant and negatively related to the return on assets. However, when it comes to days in inventory for finished products (FIGC), that relationship is significant at the limit of significance ($p=0.051$). Considering these parameters, it can be noticed that they differ from one another in the impact they have on the return on assets of industrial processing companies. In the light of data from Table 6, increasing the days in inventory for intermediate products and work-in-progress has the strongest (and negative) impact on ROA (Model 2). Indeed, a one-unit increase in that cycle (WIPC) resulted in a reduction of ROA by 0.094 percentage points. In contrast, an increase in days in inventory for raw and other materials (Model 1), finished products (Model 3), and commodities (Model 4) drove a decline in ROA by 0.049 percentage points (RMIC), 0.013 percentage points (FGIC) and 0.018 percentage points (GIC), respectively. This means that increasing the days in inventory for intermediates and work-in-progress had a 2 to 7 times greater negative effect on ROA than increasing inventory days for other discrete inventory types. The

parameters of Model 5 (which uses INVTC, aggregated inventories, as the exogenous variable for ROA) suggest that financial benefits can be derived from reducing the inventory cycles. In the light of this model, a one-unit increase in the days in inventory for total stocks entailed a reduction in ROA by ca. 0.021 percentage points.

Table 6. *Parameters of return on assets (ROA) models¹ for the manufacturing industry as a whole.*

Variables and tests	Model 1	Model 2	Model 3	Model 4	Model 5
ROA _{t-1}	-0.184 (0.089)	-0.107 (0.276)	-0.169 (0.093)	-0.148 (0.098)	-0.145 (0.123)
ROS	1.192 (0.000)	1.127 (0.000)	1.106 (0.000)	1.143 (0.000)	1.216 (0.000)
QR	-1.253 (0.008)	-1.495 (0.040)	-0.699 (0.013)	-0.792 (0.019)	-1.431 (0.024)
SFA	-0.124 (0.000)	-0.125 (0.000)	-0.092 (0.000)	-0.105 (0.000)	-0.127 (0.000)
ICEQ	0.004 (0.823)	0.009 (0.620)	0.035 (0.099)	0.026 (0.101)	-0.013 (0.617)
lnTA	-0.181 (0.134)	0.120 (0.146)	-0.019 (0.852)	-0.837 (0.395)	-0.183 (0.109)
ΔS	0.014 (0.003)	0.014 (0.005)	0.017 (0.000)	0.015 (0.004)	0.011 (0.014)
RMIC	-0.049 (0.000)				
WIPC		-0.094 (0.000)			
FGIC			-0.032 (0.051)		
GIC				-0.019 (0.000)	
INVTC					-0.021 (0.000)
constant	12.99 (0.000)	9.11 (0.000)	8.09 (0.000)	9.48 (0.000)	13.40 (0.000)
AR-2 ²	-1.07 (0.286)	-1.48 (0.136)	-1.38 (0.168)	-1.20 (0.230)	-1.47 (0.143)
Hansen's J ³	0.72 (0.868)	0.41 (0.939)	0.39 (0.942)	0.51 (0.917)	1.06 (0.786)
Instruments	12	12	12	12	12
Observations	404	404	404	404	404
Groups	69	69	69	69	69

¹The values in brackets indicate the level of significance of the variables or tests. ²AR-2 is a serial correlation test of second order using residuals of first differences, asymptotically distributed as $N(0,1)$ under null hypothesis of no serial correlation. ³Hansen's J-test is a test of over-identifying restrictions distributed asymptotically under null hypothesis of validity of instruments such as Chi-squared.

Source: Own calculations.

The models developed in this study also revealed some statistically significant relationships between ROA and selected control variables. Indeed, the analysis of data in Table 6 suggests that - what seems largely obvious - a positive and statistically significant relationship exists between the return on assets in industrial processing companies and the return on sales (ROS) and the growth rate of sales proceeds (ΔS). In turn, the structure of assets (determined by a large share of physical assets in total assets, SFA) and a conservative financial policy, reflected by a high liquidity ratio (QR), have an adverse impact on ROA.

Table 7 presents the regression parameters of the return on assets, estimated based on data for small industrial processing enterprises together with appropriate tests and statistics. The second-order autocorrelation (AR-2) test results presented in the Table show that moment conditions used in the estimation process are correct ($p=0.118-0.242$). The models' specification was also validated using Hansen's J-test, which

found no correlation between instrumental variables and the random effect in the models ($p=0.182-0.310$).

Table 7. *Parameters of return on assets (ROA) models¹ for small enterprises.*

Variables and tests	Model 1	Model 2	Model 3	Model 4	Model 5
ROA _{t-1}	-0.049 (0.420)	-0.048 (0.404)	-0.038 (0.891)	0.044 (0.372)	0.027 (0.623)
ROS	1.169 (0.000)	1.159 (0.000)	1.099 (0.000)	1.149 (0.000)	1.213 (0.000)
QR	-2.549 (0.000)	-2.487 (0.000)	-2.251 (0.001)	-1.552 (0.010)	-2.268 (0.000)
SFA	-0.168 (0.000)	-0.174 (0.000)	-0.139 (0.000)	-0.132 (0.000)	-0.157 (0.000)
ICEQ	-0.011 (0.475)	-0.001 (0.961)	-0.014 (0.339)	-0.024 (0.191)	-0.014 (0.445)
lnTA	0.126 (0.899)	0.435 (0.082)	0.143 (0.673)	0.338 (0.160)	0.105 (0.537)
ΔS	0.006 (0.005)	0.005 (0.058)	0.010 (0.001)	0.007 (0.015)	0.035 (0.215)
RMIC	-0.048 (0.000)				
WIPC		-0.138 (0.000)			
FGIC			-0.061 (0.004)		
GIC				-0.023 (0.000)	
INVTC					-0.024 (0.000)
constant	14.48 (0.000)	9.62 (0.000)	9.79 (0.000)	6.77 (0.000)	12.29 (0.000)
AR-2 ²	-1.17 (0.242)	-1.46 (0.143)	-1.56 (0.118)	-1.27 (0.204)	-1.34 (0.180)
Hansen's J ³	9.41 (0.225)	8.75 (0.271)	9.89 (0.195)	10.1 (0.182)	8.26 (0.310)
Instruments	16	16	16	16	16
Observations	134	134	134	134	134
Groups	23	23	23	23	23

¹The values in brackets indicate the level of significance of the variables or tests. ²AR-2 is a serial correlation test of second order using residuals of first differences, asymptotically distributed as $N(0,1)$ under null hypothesis of no serial correlation. ³Hansen's J-test is a test of over-identifying restrictions distributed asymptotically under null hypothesis of validity of instruments such as Chi-squared.

Source: Own calculations.

In the small enterprise sector, just like in the general population, all inventory cycles used in this study prove statistically significant and negatively related to the return on assets. Moreover, in this company size class, the strength of the impact of particular inventory cycles is clearly heterogeneous. In the light of data from Table 7, increasing the days in inventory for intermediate products and work-in-progress has the strongest (and negative) impact on ROA in the small enterprise sector (Model 2). Indeed, a one-unit increase in that cycle (WIPC) resulted in a reduction of ROA by 0.138 percentage points. In contrast, an increase in days in inventory for raw and other materials (Model 1), finished products (Model 3), and commodities (Model 4) drove a decline in ROA by 0.048 percentage points (RMIC), 0.061 percentage points (FGIC) and 0.023 percentage points (GIC), respectively. This means that increasing the days in inventory for intermediates and work-in-progress had a 2 to 6 times greater negative effect on ROA than increasing the days in inventory for other discrete inventory types in the small enterprise sector. The parameters of Model 5 (which uses INVTC, the aggregated inventories) suggest that potential positive financial effects can be derived from reducing the inventory cycles. In the light of this model, a one-unit increase in

the days in inventory for total stocks entailed a reduction in ROA by ca. 0.024 percentage points.

The parameters of the models discussed above also revealed some statistically significant relationships between ROA and selected control variables (Table 7). Indeed, just like in the general population, a positive and statistically significant relationship exists between the return on assets in small industrial processing companies and the return on sales (ROS) and the growth rate of sales proceeds (ΔS). In turn, the structure of assets (determined by a large share of physical assets in total assets, SFA) and a conservative financial policy, reflected by a high liquidity ratio (QR), have an adverse impact on ROA in this enterprise size class.

Table 8 presents the regression parameters for the return on assets, as estimated for medium-sized industrial processing companies, together with appropriate tests and statistics. The second-order autocorrelation (AR-2) test results presented in the Table show that moment conditions used in the estimation process are correct ($p=0.101-0.989$). The specification of all models was also validated using Hansen's J-test, which provides grounds for concluding that no correlation exists between instrumental variables and the random effect in the models ($p=0.182-0.641$).

In medium-sized industrial processing enterprises, the parameters of regression models (Table 8) suggest that a statistically significant and negative relationship exists between the return on assets and: the days in inventory ratio for raw and other materials (RMIC); the days in inventory ratio for intermediates and work-in-progress (WIPC); and the days in inventory ratio for commodities (GIC); whereas the relationship with the days in inventory ratio for finished products is insignificant (FGIC, $p=0.210$).

Considering the coefficients of regression of statistically significant variables, it can be noticed that extending the days in inventory for intermediates and work-in-progress had the strongest (and negative) effect on changes in the return on assets in this company size class. A one-unit increase in that cycle translated into an average reduction in ROA by 0.088% (Model 2). In turn, when it comes to extending the days in inventory for raw and other materials (RMIC) and commodities (GIC), the reduction was much smaller, namely 0.039% (Model 1) and 0.017% (Model 4), respectively. This means that in the medium-sized enterprise sector, increasing the days in inventory for intermediates and work-in-progress had a 2 to 4 times greater negative effect on ROA than increasing the days in inventory for other discrete inventory types.

The parameters of Model 5 (which uses INVTC, aggregated inventories, as the exogenous variable) suggest that potential financial benefits can be derived from reducing the inventory cycles. Based on this model, it can be concluded that a one-unit increase in the days in inventory for total stocks in this company size class entailed an average reduction in ROA by ca. 0.021 percentage points.

Table 8. *Parameters of return on assets (ROA) models¹ for medium-sized enterprises*

Variables and tests	Model 1	Model 2	Model 3	Model 4	Model 5
ROA _{t-1}	0.051 (0.610)	0.184 (0.106)	0.231 (0.031)	0.130 (0.292)	-0.028 (0.758)
ROS	0.972 (0.000)	1.001 (0.000)	0.985 (0.000)	1.084 (0.000)	1.094 (0.000)
QR	-1.698 (0.003)	-2.180 (0.000)	-2.014 (0.001)	-1.854 (0.003)	-2.386 (0.000)
SFA	-0.107 (0.000)	-0.101 (0.000)	-0.084 (0.000)	-0.097 (0.000)	-0.125 (0.000)
ICEQ	-1.774 (0.016)	-0.576 (0.032)	-0.089 (0.022)	-0.114 (0.001)	-2.225 (0.001)
lnTA	-0.124 (0.498)	0.081 (0.601)	0.289 (0.181)	0.227 (0.272)	-0.109 (0.547)
ΔS	0.018 (0.042)	0.019 (0.043)	0.011 (0.031)	0.021 (0.008)	0.021 (0.002)
RMIC	-0.039 (0.000)	-0.088 (0.000)	-0.026 (0.210)	-0.017 (0.000)	-0.020 (0.000)
WIPC					
FGIC					
GIC					
INVTC					
constant	14.53 (0.000)	8.26 (0.002)	3.90 (0.047)	5.63 (0.076)	17.26 (0.000)
AR-2 ²	-1.64 (0.101)	-1.36 (0.173)	-1.49 (0.137)	0.02 (0.989)	-1.25 (0.213)
Hansen's J ³	5.16 (0.641)	10.12 (0.182)	6.10 (0.528)	7.03 (0.426)	7.72 (0.358)
Instruments	16	16	16	16	16
Observations	134	134	134	134	134
Groups	23	23	23	23	23

¹The values in brackets indicate the level of significance of the variables or tests. ²AR-2 is a serial correlation test of second order using residuals of first differences, asymptotically distributed as $N(0,1)$ under null hypothesis of no serial correlation. ³Hansen's J-test is a test of over-identifying restrictions distributed asymptotically under null hypothesis of validity of instruments such as Chi-squared.

Source: Own calculations.

The models developed in this study also revealed some statistically significant relationships between ROA and most control variables (Table 8). Indeed, a positive and statistically significant relationship exists between the return on assets in industrial processing companies of this size class and the return on sales (ROS) and the growth rate of sales proceeds (ΔS). In turn, the structure of assets (determined by a large share of physical assets in total assets, SFA), an increase in liquidity (QR), and a greater financial leverage ratio (ICEQ) have an adverse impact on ROA.

Table 9 presents the regression parameters of the return on assets, estimated based on large industrial processing enterprises. The AR-2 test results show that moment conditions used in the estimation process are correct ($p=0.118-0.722$). The models' structure was also validated using Hansen's J-test, which justifies that no correlation exists between instrumental variables and the random effect in the models ($p=0.119-0.623$).

Table 9. *Parameters of return on assets (ROA) models¹ for large enterprises*

Variables and tests	Model 1	Model 2	Model 3	Model 4	Model 5
ROA _{t-1}	0.162 (0.228)	0.058 (0.577)	0.052 (0.757)	0.021 (0.886)	-0.077 (0.583)
ROS	0.902 (0.000)	0.896 (0.000)	0.832 (0.000)	0.864 (0.000)	1.036 (0.000)
CR	-1.757 (0.003)	-1.286 (0.006)	-0.548 (0.011)	-0.756 (0.017)	-1.450 (0.012)
SFA	-0.070 (0.000)	-0.074 (0.000)	-0.011 (0.028)	-0.020 (0.032)	-0.073 (0.000)

ICEQ	-0.375 (0.536)	-0.581 (0.492)	0.150 (0.887)	0.865 (0.256)	-1.029 (0.175)
lnTA	-0.259 (0.018)	-0.103 (0.042)	-0.021 (0.195)	-0.261 (0.012)	-0.557 (0.003)
ΔS	0.015 (0.038)	0.032 (0.001)	0.035 (0.020)	0.032 (0.020)	0.021 (0.031)
RMIC	-0.057 (0.000)				
WIPC		-0.068 (0.000)			
FGIC			-0.036 (0.205)		
GIC				-0.006 (0.012)	
INVTCT					-0.025 (0.000)
constant	11.30 (0.001)	9.04 (0.000)	4.25 (0.365)	3.20 (0.236)	16.53 (0.000)
AR-2 ²	-1.17 (0.242)	-0.36 (0.722)	-1.46 (0.143)	-1.56 (0.118)	-1.64 (0.102)
Hansen's J ³	11.51 (0.119)	9.89 (0.195)	8.14 (0.320)	6.69 (0.462)	5.31 (0.623)
Instruments	16	16	16	16	16
Observations	134	134	134	134	134
Groups	23	23	23	23	23

¹The values in brackets indicate the level of significance of the variables or tests. ²AR-2 is a serial correlation test of second order using residuals of first differences, asymptotically distributed as $N(0,1)$ under null hypothesis of no serial correlation. ³Hansen's J-test is a test of over-identifying restrictions distributed asymptotically under null hypothesis of validity of instruments such as Chi-squared.

Source: Own calculations.

In large industrial processing enterprises—just like in the medium-sized class—the parameters of regression models (Table 9) suggest that a statistically significant and negative relationship exists between the return on assets and: the days in inventory ratio for raw and other materials (RMIC); the days in inventory ratio for intermediates and work-in-progress (WIPC); and the days in inventory ratio for commodities (GIC); whereas the relationship with the days in inventory ratio for finished products is insignificant (FGIC, $p=0.205$). In this enterprise size class, too, increasing the days in inventory for intermediate products and work-in-progress and the days in inventory for raw and other materials (RMIC) had the strongest (and negative) impact on changes in ROA. A one-unit increase in these cycles translated into an average reduction in ROA by 0.068% (Model 2) and 0.057% (Model 1).

In turn, when it comes to extending the days in inventory for commodities (GIC), the reduction was considerably smaller, namely 0.006% (Model 4). This means that in the large enterprise sector, increasing the days in inventory for intermediates and work-in-progress and raw and other materials had a 9 to 11 times greater negative effect on ROA than increasing the days in inventory commodities. The parameters of Model 5, too, reveal the purposefulness of reducing the inventory cycles. Based on this model, it can be concluded that a one-unit increase in the days in inventory for total stocks (INVTCT) in this company size class entailed an average reduction in ROA by ca. 0.025 percentage points, i.e., to an extent comparable to what is observed in other size classes of industrial processing enterprises.

The models developed in this study also revealed some statistically significant relationships between the ROA of large enterprises and most control variables. Indeed, a positive and statistically significant relationship exists between the return

on assets in this company size class and the return on sales (ROS) and the growth rate of sales proceeds (ΔS). In turn, the structure of assets (determined by a large share of physical assets in total assets, SFA), an increase in liquidity (QR), and greater company size (measured with assets value, $\ln TA$) have an adverse impact on ROA.

5. Concluding Remarks

A wide variety of factors determines the economic and financial performance of enterprises. These include the inventory management policy, which is designed to set a reasonable level and structure of stocks. However, in practice, inventory management strategies differ strongly from one another due to various reasons, including the type of business, company size, industry, and the inventory management methods in place (e.g., Just in Time, Lean Management, ABC method, XYZ method, Economic Order Quantity, Materials Requirements Planning, Distribution Requirements Planning). Because of these conditions, both the direction and strength of impact the inventories have on financial performance can vary across enterprises.

This research project revealed that the Polish industrial processing sector witnessed moderate though noticeable changes in the inventory mix over the study period. The findings suggest that the share of raw and other materials and intermediate products and work-in-progress followed a weak growth trend while the share of finished products and commodities declined at a clearly faster rate. However, these changes did not essentially affect the inventory mix. Both at the beginning and end of the study period, raw and other materials and finished products remained the key components of the Polish industrial processing sector's inventory mix, making up ca. 47% and 28%, respectively, of the total inventory value. This means these categories consistently play a major role in inventory management in the industrial processing sector. The great importance of managing these very discrete inventory types is corroborated by analyzing inventory cycles, which suggests that the corresponding days in inventory ratios were the greatest determinants for the day's inventory sales for total stocks.

This study also found that the inventory mix changes and the management efficiency of these assets, measured with the respective day's sales ratios, reveal a series of differences between company size groups. The share of inventories in total assets and current assets was relatively smaller in the small enterprise sector and followed a moderate yet noticeable downward trend. In turn, when it comes to medium and large enterprises, the corresponding shares were higher and followed an upward trend in the study period. The differences in the levels of, and trends followed by, ratios covered by this study are also reflected in the inventory mix. The small enterprise sector saw an increase in the share of intermediate products and work-in-progress, whereas the share of finished products and commodities declined at a similar rate. In turn, as regards medium enterprises, the inventory mix was quite stable in the study period. However, what makes large industrial processing companies stand apart is the relatively strongest decline in the share of finished products in total inventories.

Findings from this study also revealed some considerable differences in inventory management efficiency (measured with the days in inventory ratio) and in the trends followed by the changes (hypothesis 1). Generally, between 2013 and 2019, all three enterprise size classes witnessed an increase in inventory ratio for total stocks; this suggests a deterioration in how these assets are managed. That adverse trend is most noticeable in large enterprises; although their days in inventory ratio for total stocks was the shortest in all years, it went up by more than 17%.

However, despite that trend, inventory management's efficiency (measured with the days in inventory ratio for total stocks) in large enterprises was 25–30% higher in all years covered by this study. In turn, considering the sub-cycles (hypothesis 2), it was noted that the days in inventory ratios for raw and other materials and commodities were decisive for the days in inventory ratios for total stocks; the above is true for all company size classes. Moreover, these ratios' adverse trend (due to them becoming longer) was the strongest determinant of unfavorable changes in the days in inventory ratio for total stocks in all the large, medium, and small industrial processing companies.

The characteristics of inventories were also found to differ considerably between industrial processing sub-sectors; note that these differences were much greater than between company size classes. The greatest differences between industrial processing sub-sectors exist in the days in inventory ratio for intermediates and work-in-progress and share that discrete inventory type in total stocks. The days in inventory ratio for this type of inventory is particularly long in the manufacture of other transport equipment. In turn, the fastest rotation of intermediates and work-in-progress, i.e., the shortest days in inventory, was reported in the manufacture of tobacco products, a sub-sector where that discrete inventory type is of marginal importance.

Industrial processing sub-sectors also differ quite strongly in the inventory ratio for raw and other materials, finished products, and commodities. The differences in the duration of inventory sub-cycles entail quite pronounced differences between industrial processing sub-sectors in the days in inventory ratio for total stocks, which fell within a broad interval spanning from ca. 70 days (manufacture of food products, manufacture of coke and refined petroleum products) to over 200 days (manufacture of leather and related products, manufacture of pharmaceutical products, manufacture of wearing apparel).

As demonstrated by econometric analyses, statistically significant causative links exist between days in inventory and financial performance (hypothesis 3-4). Based on the panel regression models developed, it was demonstrated that increasing the days in inventory harms the return on assets. The study also proved the usefulness of taking the inventory mix into account. Generally, increasing the days in inventory for particular discrete inventory types also harmed the return on assets in industrial processing companies. Furthermore, based on regression parameters, this study also demonstrated that increasing the days in inventory ratios for intermediate products

and work-in-progress and raw and other materials had the greatest (and negative) impact on ROA. Indeed, extending these inventory cycles was much more determinant for ROA than an increase in days in inventory for other discrete inventory types. The above is true both for the industrial processing sector as a whole and for each company size class.

References:

- Alrjoub, A.M.S., Ahmad, M.A. 2017. Inventory management, cost of capital and firm performance: evidence from manufacturing firms in Jordan. *Investment management and financial innovations*, 14(3), 4-14.
- Arellano, M., Bond, S. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, 58, 277-297.
- Balakrishnan, R., Linsmeier, T.J., Venkatachalam, M. 1996. Financial benefits from JIT adoption: Effects of customer concentration and cost structure. *The Accounting Review*, 71(2), 183-205.
- Bank for Accounts of Companies Harmonised. 2020. European database of aggregate information on non-financial corporations. European Central Bank. Retrieved from: <http://www.bachesd.banque-france.fr>.
- Bendig, D., Brettel, M., Downar, B. 2018. Inventory component volatility and its relation to returns. *International Journal of Production Economics*, 200, 37-49.
- Blundell, R., Bond, S. 1998. Initial conditions and moment restriction in dynamic panel data models. *Journal of Econometrics*, 87, 115-143.
- Boute, R.N., Lambrecht, M.R., Lambrechts, O., Sterckx, P. 2007. An analysis of inventory turnover in the Belgian manufacturing industry. SSRN Library, 1-12. Retrieved from: <https://ssrn.com/abstract=1089005>.
- Cannon, A.R. 2008. Inventory improvement and financial performance. *International Journal of Production Economics*, 115(2), 581-593.
- Capkun, V., Hameri, A.P., Weiss, L.A. 2009. On the relationship between inventory and financial performance in manufacturing companies. *International Journal of Operations & Production Management*, 29(8), 789-806.
- Chan, H., Frank, M.Z., Wu, O.Q. 2005. What actually happened to the inventories of American companies between 1981 and 2000? *Management Science*, 51(7), 1015-1031.
- Dong, H.P., Su, J. 2010. The relationship between working capital management and profitability: a Vietnam case. *International Research Journal of Finance and Economics*, 49, 62-71.
- Eroglu, C., Hofer, C. 2011. Inventory types and firm performance: vector autoregressive and vector error correction models. *Journal of Business Logistics*, 32(3), 227-239.
- Financial results of non-financial enterprises. 2013-2019. Central Statistical Office, Poland, Warsaw. Retrieved from: <https://stat.gov.pl/en/topics/economic-activities-finances/>.

- Ganas, I., Hyz, A. 2015. Inventory management and firm's performance during the period of financial constraints: an empirical analysis of SME sector in Greece. The European Business and Management Conference 2015, Brighton, United Kingdom Official Conference Proceedings. Retrieved from: <https://papers.iafor.org/proceedings/conference-proceedings-ebmc2015/>.
- Gaur, J., Bhattacharya, S. 2011. The relationship of financial and inventory performance of manufacturing firms in Indian context. *California Journal of Operations Management*, 9(2), 70-77.
- Gaur, V., Fisher, M.L., Raman, A. 2005. An econometric analysis of inventory turnover performance in retail services. *Management Science*, 51(2), 181-194.
- Gołaś, Z., Bieniasz, A. 2016. Empirical analysis of the influence of inventory management on financial performance in the food industry in Poland. *Engineering Economics*, 27(3), 264-275.
- Gołaś, Z. 2020. Effect of inventory management on profitability: evidence from the Polish food industry: Case study. *Agricultural Economics – Czech*, 66, 234-242.
- Gołaś, Z. 2020. Impact of working capital management on business profitability: Evidence from the Polish dairy industry. *Agricultural Economics – Czech*, 66, 278–285.
- Hsiao, C. 1985. Benefits and limitations of panel data. *Economic Review*, 4, 121-174.
- Isaksson, H.D.M., Seifert, R.W. 2014. Inventory leanness and the financial performance of firms. *Production Planning & Control*, 25(12), 999-1014.
- Koumanakos, D.P. 2008. The effect on inventory management on firm performance. *International Journal of productivity and Performance Management*, 57(5), 355-369.
- Kempny, D. 1995. Koszty zapasów (Inventory costs). *Gospodarka materiałowa i logistyka*, 7(8), 9-17.
- Kisperska-Moroń, D. 1995. *Czynniki kształtujące poziom i strukturę zapasów w przedsiębiorstwach* (Factors affecting the level and structure of corporate inventories). *Gospodarka materiałowa i logistyka*, 11, 11-20.
- Kolias, G.D, Dimelis, S.P, Filios, V.P. 2011. An empirical analysis of inventory turnover behaviour in Greek retail sector: 2000-2005. *International Journal of Production Economics*, 133(1), 143-153.
- Lazaridis, I., Tryfonidis, D. 2006. Relationship between working capital management and profitability of listed companies in the Athens stock exchange. *Journal of Financial Management and Analysis*, 19(1), 26-35.
- Lieberman, M.B., Helper, S., Demeester, L. 1999 The empirical determinants of inventory levels in high-volume manufacturing. *Production and Operations Management*, 8(1), 44-55.
- Manikas, A.S. 2017. Interdependence among inventory types and firm performance. *Operations and Supply Chain Management*, 10(2), 63-80.

- NACE Revision 2. 2008. Statistical classification of economic activities in the European Community, Methodologies and working papers,. Eurostat, European Commission. Retrieved from:
<https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF>)
- Obermaier, R., Donhauser, A. 2009. Disaggregate and aggregate inventory to sales ratios over time: the case of German corporations 1993-2005. *Logistics Research*, 1(2), 95-111.
- Padachi, K. 2006. Trends in working capital management and its impact on firms' performance: an analysis of Mauritian small manufacturing firms. *International Review of Business Research Papers*, 2(2), 45-58.
- Raheman, A., Qayyum, A., Afza, T., Bodla, M.A. 2010. Sector-wise analysis of working capital management and firm performance in manufacturing sector of Pakistan. *Interdisciplinary Journal of Contemporary Research in Business*, 2(7), 412-437.
- Ramachandran, A., Janakiraman, M. 2009. The relationship between working capital management efficiency and EBIT. *Managing Global Transitions*, 7(1), 61-74.
- Roumiantsev, S., Netessine, S. 2007. What can be learned from classical inventory models? A cross-industry exploratory investigation. *Manufacturing and Service Operations Management*, 9(4), 409-429.
- Shah, R., Shin, H. 2007. Relationships among information technology, inventory and profitability: an investigation of level invariance using sector level data. *Journal of Operations Management*, 25(4), 768-784.
- Shin, H., Wood, C.C., Jun, M. 2016. Does Effective Inventory Management Improve Profitability? Empirical Evidence from U.S. Manufacturing Industries. *International Journal of Information Systems and Supply Chain Management*, 9(3), 26-45.
- Windmeijer, F. 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1), 25-51.