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Inventory, Employment, and Productivity: Evidence from the U.S. Manufacturing Sector

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Abstract:

Inventory investment represents one of the main determinants of employment. In the context of extensive and infrequent productivity shocks, inventory investment changes can have large effects on total employment. We investigate the relationship between inventory and employment at specific levels of total factor productivity using U.S. manufacturing sector data. We found that inventory increases total employment in the U.S. manufacturing sector significantly. The marginal effect of inventories on total employment increases at the total factor productivity level, which is explained by firms' tendency to accumulate inventories in periods of high productivity to compensate for periods of adverse productivity shocks. But to do so, firms hire additional workers to carry out the increase in production.

Keywords **—Inventory, total factor productivity, Employment.**

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I. INTRODUCTION

According to data from the Bureau of Economic Analysis, the United States manufacturing sector remains a critical component of Gross Domestic Product (GDP) despite the sector's decline from 24.3% of US GDP in 1970 to approximately 11% in 2020. The National Association of Manufacturers (2019) estimates that 8.51% of the U.S. workforce is employed by the manufacturing sector, highlighting the non-trivial influence that inventory level fluctuations can have on manufacturing industry employment variations. The far-reaching consequences of an inter-relationship between variations in manufacturing inventory levels and within-sector employment levels invite investigation into the specific factors affecting this relationship. These far-reaching consequences are also highlighted through the comprehensive reforms promoted by recent government administrations to revitalize the country's manufacturing sector.

Across several studies analysing inventory and business cycle dynamics, it is well-known and generally agreed that inventories are volatile and move procyclically ([1], [2], [3], [4]-[5]). In a now-famous remark by Alan Blinder, former Governor of the Federal Reserve System, he stated that "the business cycle, to a surprisingly large extent, is an inventory cycle." It follows that the timing of inventory investment over the business cycle may play an important role in accounting for GDP changes and other standard aggregate economic variables. Despite broad consensus on the synchronization between consumer demand and GDP, the theoretical underpinnings do not support any widespread agreement between those who think that inventory is a destabilizing force for production and claim that it is a contributor. In the context of extensive and infrequent productivity shocks, inventory investment changes can have large effects on total employment.

While most studies seek to explain the dynamics between inventories and sales fluctuations or inventories and business cycle changes, few papers connect variations in inventories with labour market outcomes. Among the papers most closely related to this work ([6],[7]) consider inventories a form of good market friction where investment in inventories is a residual rather than an optimal decision of the firm. Focusing on firm-level analysis, Gaur et al. [8]investigate the correlation between inventory turnover with gross margin, capital intensity, and sales forecast error. Our paper differs from theirs in the following way. We control differential time trends in employment and industry-specific unobserved heterogeneity to study the causal effects of inventory on employment. This difference matters because it offers the possibility to capture intrinsic changes to different industries instead of firm-specific.

This paper investigates the importance of accounting for inventory adjustments over 473 industries in the manufacturing sector on total employment from 1958 to 2011. To do so, we allow inventory effects to differ at the level of total factor productivity. We construct two exogenous and relevant instruments to isolate some exogenous inventory and productivity variation sources. They reflect non-manufacturing industry-specific inventory changes that have differential effects on industries due to dissimilarities in the manufacturing and non-manufacturing sector.

The rest of this paper is organized as follows. Section II reviews existing related literature and briefly discuss their conclusions while citing a hypothetical relevant example to illustrate real-world decision making by a firm that holds inventory. In Section III, we explain our data sources and highlight a critical industrial classification change in the United States in the context of our research. In Section IV, we state the various model specifications we use to examine the causal effects of inventory on total employment using aggregated data from Section III. Section V details the results from our models with a particular focus on robustness checks. We conclude our research in Section VI with a summary of the practical implications of the results we obtain from our analyses.

II. RELATED LITERATURE[1]

II.I. Inventory, Sales, and Production

In traditional Real Business Cycles (RBC) models, lifetime profit maximization is the firm's assumed goal. This goal, however, most of the time, passes by expanding its level of production.A change in the production level can result from a modification in the stock of equipment and materials or labour stock. The production-smoothing model of inventories assumes that adjusting the production level is not without consequence for a firm that wants to minimize its costs. Hiring new workers or new equipment to meet the demands can be very costly. More simply, a firm like DELL knows that its computers' sales are likely to go up during black Friday. But the company also knows that in November, one month before the Christmas period, the cost of inputs and labour are likely to be higher.

Consequently, DELL can produce more and accumulate inventories before black Friday and then sell off the products during the Black Friday and Christmas period. Hence, the production-smoothing model predicts that instead of varying

[1]There is a literature that relates inventory to production. But there is a separate one that relates inventory to productivity.

production abruptly and frequently to match with sales, firms use inventory as a buffer to meet sales. Adjusting production is costly, and the cost depends on the type and the extent of adjustment required. That being the case, firms tend to vary production less than sales.[2] In aggregation, this could give rise to volatility in sales being more than volatility in GDP. Like any other model, this one has its shortcomings. Using U.S. quarterly data from the first quarter of 1954 to the fourth one of 2002, Khan [9] has found that the correlation between final sales and inventory investment is positive. This would imply that production has higher variability than sales, which would contradict the production-smoothing model of inventories where inventories play a role of buffer protecting production from fluctuations in sales. Eichenbaum [10] and Ramey [11] have proposed different solutions to fit the facts' model.

Unlike the production smoothing argument, whose focus is on the adjustment costs, the (S, s) model assumes that there are fixed costs related to orderinggoods.[3] In this model, the fixed cost will arise when firms request or undertake the delivery of goods. So, to reduce those costs, firms tend to order substantial quantities of relevant products and accumulate inventories infrequently. Furthermore, the (S, s) model seems to match the facts regarding either a positive or negative relationship between inventories and sales. There is a nonlinear aspect of this model. For some firms, the co-movements between sales and inventories are positive while they are negative for others. Caplin [12] found that final sales and inventories move together, which had contradicted that retail sector inventories protect manufacturing firms from fluctuations in sales, as variability in production surpasses variability in sales. A more recent work by Thomas et al. [13] found that inventory investment and sales are positively related.

II.II. Inventory and Productivity

Gaur et al. [8] consider inventory turnover an alternative metric for inventory productivity.[4] They define inventory turnover as the ratio of the cost of goods sold to the average inventory level. When investigating the correlation between inventory turnover with gross margin, capital intensity, and sales forecast error, they find a 66.7% within-firm variation and 97.2% of the total variation in inventory turnover. However, at the macroeconomics level, regarding total factor productivity, Lieberman et al.[14] use U.S. auto assemblers and argue for a strong negative relationship between inventory and productivity growth. Furthermore, Chang et al. [15] find that the relationship between inventory and employment is positive. But, a priori, it seems to be the case that when productivity growth is high, firms tend to hire more employees to produce more goods. And when the production changes are more significant than variation in demands, high productivity leads to increases in inventory. In times of low productivity growth in the economy, to face the market demand, firms decrease the production level by selling more of the goods piled up in a period of high productivity. This is expected to hurt total employment.

[2]This is one of the most important implication of the model and one of the controversial as well. we said above that Production= Sales + Net Inventory Investment (NII). So, variance (Production)= variance(sales)+ variance (NII)+2Covariance (sales, NII). Saying that firms tend to vary production less than sales, is implicitly saying that the covariance between sales and net inventory investment is negative.

[3]As Herbert Scarf (1959) suggested, firms allow inventory to change to an upperlevel labelled S and a lower level labelled s, where S is the level of inventories held by firm after it has restocked. According to the author, the firms let their stocks of inventories fluctuate until it reaches the lower level s.

[4]This is basically productivity at the firm level, which is different from total factor productivity at the macroeconomic level.

III. DATA

This paper uses the NBER-CES Manufacturing Industry Database, which contains annual data for the U.S. manufacturing sector from 1958 to 2011. Becker, Gray, and Marvakov build this database in 2016. They use data from various sources such as the U.S Census Bureau, Bureau of Economic Analysis (BEA), and Bureau of Labor Statistics. We obtain most of the variables from the Annual Survey of Manufactures (ASM), which contains 50,000 to 65,000 establishments selected from 350,000 establishments included in the Census of Manufactures (CMF). We obtained the following variables from the ASM: total employment (emp), total payroll (pay), production workers (prode), production worker hours (prodh), production worker wages (prodw), the full value of shipments (vship), the total cost of materials (matcost), total value added (vadd), new capital expenditure (invest), end-of-year inventories (invent), and the cost of fuel and electricity (energy). The authors use the perpetual inventory method to determine the industry's real stock of equipment (equip), structures (plant), and total real capital stock.

It is worth noting that the industrial classification had undergone two substantial significant changes in 1972 and 1987. It then moved from the Standard Industrial Classification (SIC) in 1987 to the North American Industrial Classification System (NAICS) in 1997. As expected, there was some entry, exit, and realignment of manufacturing industries. A new variable (PCTNMFG) was created to account for this exogenous change in the classification. It measures the fraction of the SIC manufacturing industry's shipments that moved to a non-manufacturing industry NAICS (or vice versa).

IV. MODEL

IV.I. Model Specification

In this paper, we use a Panel Fixed-Effect model to assess the impact of inventories on total employment at specific productivity levels. Our main specification can be expressed as follows: $\log(emp_{it}) = \beta_0 + \beta_1 \log(invent_{it}) + \beta_2 \log(tfp5_{it}) + \beta_3 \log(invent_{it}) * \log(tpf5_{it}) + \beta_4 X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$ for industry i (i=1, 2,…, 473) and time t (t=1958,…, 2011), where the dependent variable log(emp_{it}) is the logarithm of the total employment in 1000s in industry i at time t. The main independent variables are log($invent_{it}$) and log($tfp5_{it}$), where the first accounts for the log of end-of-year inventories in $1 million in industry i at time t while the second represents the log of total factor productivity in industry i at time t. The coefficients of interest are β_1, β_2, and β_3. On the one hand, the coefficient β_1 captures the ceteris paribus effect of a one percent increase in end-of-years inventories on total employment in 1000s in the U.S. when the log total factor productivity is zero (or when tfp5=1). On the other hand, β_3 is an elasticity that allows the effects of inventory on total employment to differ at specific levels of productivity shocks.

Besides, we control for industries observable characteristics (X_{it}) such as production worker hours in millions of U.S. dollar, total capital expenditure of industry i at time t in millions, cost of electricity and fuels of industry i at time t in millions U.S. dollar, the total material cost of industry i at time t in millions U.S. dollar, and real capital for equipment and structures of industry i at time t in millions U.S. dollar. We also control for industry-specific unobserved effect through α_i, which captures all unobserved time-constant factors affecting total employment, such as unobserved industry-specific management culture. Finally, λ_t accounts for differential time trends in total employment that are invariant at the industry level.

Causal identification would require that log of end-of-year inventories be uncorrelated with the outcome variable log of total employment. This requires that the E(ε_{it} | $\log(invent_{it})$, $\log(tfp5_{it})$, $\log(invent_{it}) * \log(tpf5_{it}), X_{it}, \alpha_i, \lambda_t$)=0 to be satisfied. In general, there are three main reasons why endogeneity problems may arise: omitted variables, measurement errors, and reverse causality. In the case of this paper, we suspect that both inventory and total factor productivity are likely to be endogenous.

If the industry unobserved characteristics such as productive amenities, industry employment culture, and management ability vary over time, the industry unobserved heterogeneity αi included in the model will not be able to capture those factors. This may create omitted variable bias problem, which would cause endogeneity. Another potential issue is the reverse causality or simultaneity problem that may exist between inventory and employment. Inventory is likely to cause employment, and employment is also expected to affect inventory. One way to define inventory is the difference between production and sales (Inventory = Production - Sales). More employment is likely to create more goods, which, holding everything else constant, may give rise to more unsold goods, in other words, more inventory. From another perspective, according to which inventories play a role of buffer protecting production from fluctuations in sales, there is a production-smoothing argument. In periods of low productivity, firms tend to use their inventories to fulfill the demand instead of hiring new employees.

Moreover, we suspect that total factor productivity has measurement errors on top of being reversely caused by total employment. As noted by Hornbeck et al. [16], total factor productivity is a residual. Total factor productivity is estimated from a production function, and it is subject to measurement error in output and inputs. Because of the above endogeneity issues, to study the causal effects of inventory on total employment, we must isolate some sources of exogenous variation in inventory and total factor productivity by using some instruments. Mainly, we have used the same method to construct all our instruments. They rely on different identifying assumptions. Their validity is proved in the results (section V) below.

Our first instrument (pp) is an interaction term instrumental variable, reflecting non-manufacturing industry-specific inventory changes that have differential effects on industries due to differences in the manufacturing and non-manufacturing sectors. This instrument is used to get some exogenous source of variation in inventories. To construct this instrument, we multiply the fraction of the SIC manufacturing industry's shipments that moved to a non-manufacturing NAICS industry (pctnmfg) in 1997 by the total payroll in millions of U.S. dollars.[5] The identification assumption is that changes in unobserved determinants of inventories and total payroll in industries that move from SIC to a non-manufacturing industry in 1997, on average, are the same.

Our second instrument (ppw) has been created to isolate exogenous variation in total factor productivity. It is given by the production worker wages multiplied by the fraction of industry of SIC that moved to a non-manufacturing industry. The result is enough to isolate some exogenous source variation in total factor productivity. The identifying assumption is that changes in unobserved determinants of total factor productivity and total production worker wages in industries that move from SIC

[5]Becker, Gray, and Marvakov (2016) built the database that we are using in this paper. They created the pctnmfg variable because some industries were split between manufacturing and non-manufacturing in the move from SIC to NAICS in 1997.

to a non-manufacturing industry in 1997, on average, are the same.

V. RESULT AND DISCUSSION

The primary specification investigating the causal effects of inventories on total employment is reported in Table 1 below. As shown in the table below, we performed four different model specifications to investigate the causal effect of interest. Model (4) is our preferred specification, which controls for industry and year fixed effects. In Model (1), when we do not control for industry and year fixed effects, a 10 percent increase in end-of-year inventories is predicted to increase total employment in the manufacturing sector by 1.09% when the log of total factor productivity is zero. But when the log of total productivity is different from zero, the interaction term is negative. At the average total factor of productivity, the marginal effect of inventories on total employment is 0.114, which means that a 10 percent increase in inventories increases total employment in the manufacturing sector by 1.14%.

Furthermore, in Model (2), when we control for the differential time trends in employment, we realize that inventories' effect increases significantly. When the log of total factor productivity is zero (or tfp5=1), a 10 percent increase in inventories increases total employment by 6.746%. Compared to the baseline means of 3.025, this average effect represents a 22% increase in total employment. The interaction term that accounts for the impact of inventories on employment for a log productivity level different from zero becomes positive. A 10 percent increase in inventories in the manufacturing sector is predicted to increase employment by 0.275%. It is also worth noting that Model (3) and Model (1) have more or less the same point estimates. Both models did not control year-fixed effects, while Model (3) adjusts for industry fixed effects. As such, we believe that adjusting for industry-fixed effects only does not change the impact of inventories on employment significantly compared to the model with no industry and year fixed effects.

In our preferred specification (Model 4), a 10 percent increase in end-of-year inventories is predicted to increase total employment in the U.S. manufacturing sector by 6.776% when the log of total factor productivity is zero. This effect is statistically significant at the one percent significance level and is economically significant as it amounts to a 22% increase compared to the baseline means. The interaction term is positive and statistically significant at the one percent significance level. The marginal effect of inventories on total employment is given by the following equation, which depends on log total factor productivity: $\frac{\partial Log(emp_{it})}{\partial Log(invent_{it})} = 0.6676 + 0.0279 * \log{(tfp5)}$. For an average log of total factor productivity of -.09789, the marginal effect of inventories is 0.6748. As such, a 10% increase in stock increase total employment in the U.S. manufacturing sector by 6.748% at the mean of total factor productivity.

The main results show that inventories' marginal effect on total factor productivity is susceptible to the differential time trends. In all the models where we do not control for time trends, whether or not we account for industry-fixed effects, inventories' marginal effect at the average level of total factor productivity varies between 0.109 and 0.114. However, when controlling for time trends in employment, the marginal outcome at the mean of productivity varies between 0.6748 and 0.6776, which is more than six times bigger than not controlling for year fixed effects.

As highlighted above, the marginal effect of inventories on total employment is positive and total productivity is positively correlated with the marginal effect. The positive relationship between productivity and the marginal effect is explained by firms' tendency to accumulate inventories in periods of high productivity to compensate for periods of adverse productivity shocks. This is known as a cumulative behavioural effect by the firms. This cumulative behavioural effect of the firm is associated with employment because to accumulate those inventories, firms tend to hire additional workers to increase production. These results show that in their objective to maximize profits and minimize production costs, firms' decision to accumulate inventories for an eventual increase in demand is not without consequences on their number of employments. At the macroeconomic level, the increases in end-of-year inventories are consistent with the Keynesian aggregate demand model, which postulates that an increase in investment will increase aggregate demand, enhance the Gross Domestic Product, and reduce unemployment in the economy.

VI. ROBUSTNESS CHECK

Table 2 below presents the results of the first regression. As shown in the table below, the first instrument is statistically significant at a one percent level, while the second instrument is only significant at the one percent level. In terms of validity, we use the Hansen's J statistic test over-identifying restrictions test. According to this test, the joint null hypothesis is that the instruments are valid, i.e., uncorrelated with the error term. The excluded instruments are correctly excluded from the estimated equation.[6] Under the null, the test statistic is distributed as chi-squared in the number of over-identifying restrictions. A rejection casts doubt on the validity of the instruments. Hansen's J statistic is evaluated at 4.190 for a p-value of 0.1230, which is substantially higher than the 0.05 (5%) significance level. So, we fail to reject the null hypothesis, which means that our excluded instruments are valid.

[6] Information concerning the Hansen J statistics are obtained from Stata Help documentation.

VII. CONCLUSION

In this paper, we have revisited a critical policy question: the effects of inventories on total employment in the manufacturing sector. Starting with the Blinder et al. [1] work, previous studies have shown that inventories are essential for understanding business cycle fluctuations. While recent work has focused more on the relationship between inventories and sales, an important issue that has been neglected is the role of total factor productivity in the average total impact of inventories on employment. Our results indicate that this consideration matters. To estimate the effect of interest, we use U.S. manufacturing data from 1958 to 2011 and two instruments to solve endogeneity problems from inventories and productivity. Those instruments reflect non-manufacturing industry-specific inventory changes that have differential effects on industries due to differences in the manufacturing and non-manufacturing sector. The first stage regressions suggest that the instruments are relevant, and Hansen's J statistic shows that they are valid.

The main results show that inventories' marginal effect on total factor productivity is susceptible to the differential time trends. When controlling for year fixed effects, the marginal impact of inventories on total employment at the average of total factor productivity is six times bigger than the model without year fixed effects. In our preferred specification, we found that a 10% increase in end-of-year inventories is predicted to increase total employment in the U.S. manufacturing sector by 6.776% when the log of total factor productivity is zero. This effect is statistically significant at the one percent significance level and is economically significant as it amounts to a 22 % increase compared to the baseline means. At the average total factor productivity, a 10% increase in inventory increase total employment in the U.S. manufacturing sector by 6.748%. The marginal effect of inventories on total employment increases at the total factor productivity level, which is explained by firms' tendency to accumulate inventories in periods of high productivity to compensate for periods of adverse productivity shocks. But to do so, firms hire additional workers to carry out the increase in production. At the macroeconomic level, the increases in end-of-year inventories align with the Keynesian aggregate demand model, which posits that an increase in investment will increase aggregate demand, enhance the gross domestic product, and reduce unemployment inthe economy.

APPENDIX

Effect of Inventories and Total Factor Productivity on Total Employment in the U.S. Manufacturing Sector

TABLE I

VARIABLES	IV Model (1)	IV Model (2)	IV Model (3)	IV Model (4)
Log End-of-year Inventories	0.1090***	0.6746***	0.1031***	0.6776***
	(0.003)	(0.003)	(0.003)	(0.003)
Log Productivity* Log Inventories	-0.0513***	0.0275***	-0.0525***	0.0279***
	(0.005)	(0.003)	(0.005)	(0.003)
Constant	2.06***	0.10***	2.06***	-0.027
	(0.026)	(0.026)	(0.051)	(0.033)
Observations	25,386	25,386	25,386	25,386
Number of Industries	473	473	473	473
Mean of Dependent	3.025	3.025	3.025	3.025
$\frac{Inventories}{Mean\ Dependent}$	0.036	0.22	0.034	0.22
Control Variables	Yes	Yes	Yes	Yes
Industry F.E.	No	No	Yes	Yes
Year F.E.	No	Yes	No	Yes

*Notes: Authors' analysis using NBER-CES Manufacturing Industry Data. Each column represents a different model. The outcome variable is the log of total employment. Whenever possible, each regression controls for total payroll, production worker hours, production worker wages, value of shipments, total cost of materials, industry's real stock of equipment, and structures. The standard errors are in parenthesis. ***p<0.01, **p<0.05, *p<0.1*

TABLE II

FIRST STAGE REGRESSIONS

VARIABLES	(1) Log Inventories	(2) Log Productivity
Instrument 1 (pp)	0.0012*** (0.000)	
Instrument 2 (ppw)		0.0005* (0.000)
Constant	3.7599*** (0.057)	-0.4230*** (0.032)
Observations	25,386	25,386
Number of Industries	473	473
Control Variables	Yes	Yes
Industry F.E.	Yes	Yes
Year F.E.	Yes	Yes

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