Demand in the long-run and Technichal Change: The case of the United States after Breton Woods

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Abstract

Within the Sraffian Supermultiplier literature, only a few papers have attempted to incorporate technological change. This is primarily because modeling technological change introduces a highly complex landscape: the variety of technological changes means that theorization often struggles to yield sufficiently general results. This paper aims to address this gap, but rather than focusing solely on theoretical work, we begin with empirical evidence and interpret these findings through a theoretical model. We not only develop a demand-led model of activity levels that incorporates technological change, but we also provide empirical evidence on the technological change process observed in the post–Bretton Woods United States. Our results suggest that an increase in autonomous demand initiates a virtuous cycle of rising labor productivity.

JEL classification: E12, E22, E23, E24, E31, J21, O33, O41.

Keywords: technical change, sraffian supermultiplier, autonomous demand

1. Introduction

Few studies have incorporated technological change within the framework of the Sraffian Supermultiplier model (Serrano, 1995). This paper aims to fill this gap in the literature by introducing a demand-led activity levels model that integrates technological change.

Firstly, we aim to review all studies related to the Sraffian Supermultiplier (hereafter, SSM) that attempt to incorporate technological change (hereafter, TC). Secondly, we will estimate four scenarios involving autonomous demand shocks. The first Model (Model 1) analyzes the impact of an autonomous demand shock (government consumption and exports) on labor productivity, the level of industrial capacity utilization, inflation, and the level of industrial productive capacity. In this scenario, we will develop one case in which labor productivity is more exogenous than autonomous demand (Model 1.1) and another where autonomous demand is more exogenous than productivity (Model 1.2). In the second model (Model 2), we will analyze the impact of autonomous demand on labor productivity, the unemployment rate, inflation, and the labor force participation rate. Again, there will be two sub-scenarios: in the first, labor productivity will be more exogenous than autonomous demand (Model 2.1), while in the second, autonomous demand will be more exogenous than labor productivity (Model 2.2).

2. Literature Review

The reality is that there is a significant lack of research that incorporates technological change (TC) within the framework of the Sraffian Supermultiplier (SSM), both at the theoretical and empirical levels. This scarcity is evident across a wide range of academic studies, highlighting a considerable gap in the existing literature. Despite the importance of understanding how technological advancements interact with economic models like the SSM, very few works have explored this intersection comprehensively, leaving much room for further investigation and development in this area.

Table 1: Technical Change and the SSM

Article	Authors
Technical change, effective demand and employment	Cesaratto, Serrano and Stirati (2003)
Producto potencial y demanda en el largo plazo: hechos estilizados y reflexiones sobre el caso argentino reciente	Amico, Fiorito and Hang (2011)
Productividad cíclica y estructural: un fenómeno endógeno en Argentina entre 2003-2010	Guaita (2011)
Putting austerity to bed: Technical progress, aggregate demand and the supermultiplier	Deleidi and Mazzucato (2019)
The economics of the super-multiplier: A comprehensive treatment with labor markets	Palley (2019)
Supermultiplier, innovation and the ecosystem: a stock-flow dynamic model	Deleidi, Pariboni & Passarella (2019)
Conflicting-claims and labour market concerns in a supermultiplier SFC model	Brochier (2020)
Reverse hysteresis? Persistent effects of autonomous demand expansions.	Girardi, Paternesi Meloni & Stirati (2020)
R&D-based economic growth in a supermultiplier model	Nomaler, Spinola & Verspagen (2021)
Directed innovation policies and the supermultiplier: An empirical assessment of mission-oriented policies in the US economy	Deleidi & Mazzucato (2021)
The influence of productivity gains, their distribution, and market structure on economic growth in a Sraffian Supermultiplier model (PhD Thesis)	Di Domenico (2022)

Source: Own elaboration.

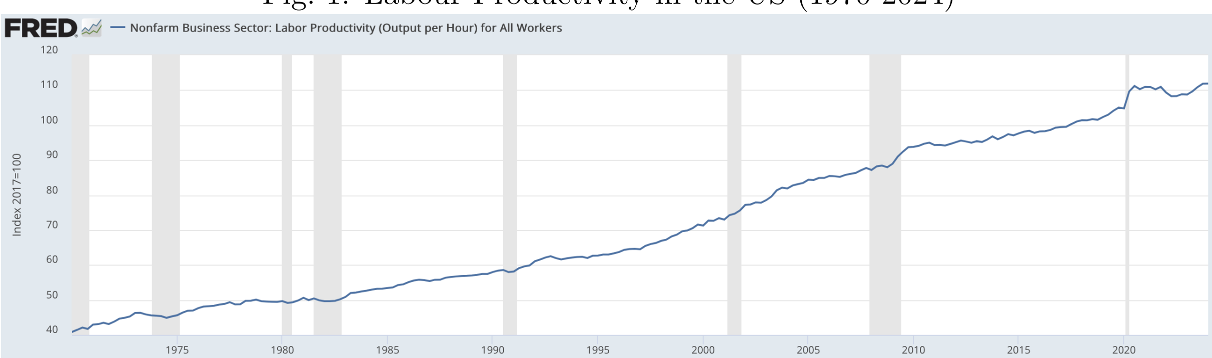
3. Empirical Evidence

3.1. Some Aggregate Stylized Facts

In this section, we provide an overview of some key stylized facts about the U.S. economy during the period under examination, spanning from 1970 to 2024. This specific timeframe has been selected for analysis because it encompasses a significant era in which the United States has maintained its position as a hegemonic global power, as highlighted by Vernengo (2021). By focusing on this period, we aim to capture the economic dynamics and influential factors that have shaped the U.S. economy over more than five decades, thereby providing a comprehensive understanding of its hegemonic status and the broader implications of its economic trends and policies during this time.

In this section, we use aggregate labor productivity as an indicator of technological change, specifically utilizing the Nonfarm Business Sector: Labor Productivity (Output per Hour) for All Workers, as detailed in Appendix A. One of the key characteristics observed during this period is the steady increase in labor productivity, which serves as one of the various measures of technological change (see Figure 1). This upward trend highlights the continuous improvements in output per hour worked, reflecting the advancements in technology and efficiency within the U.S. economy over time.

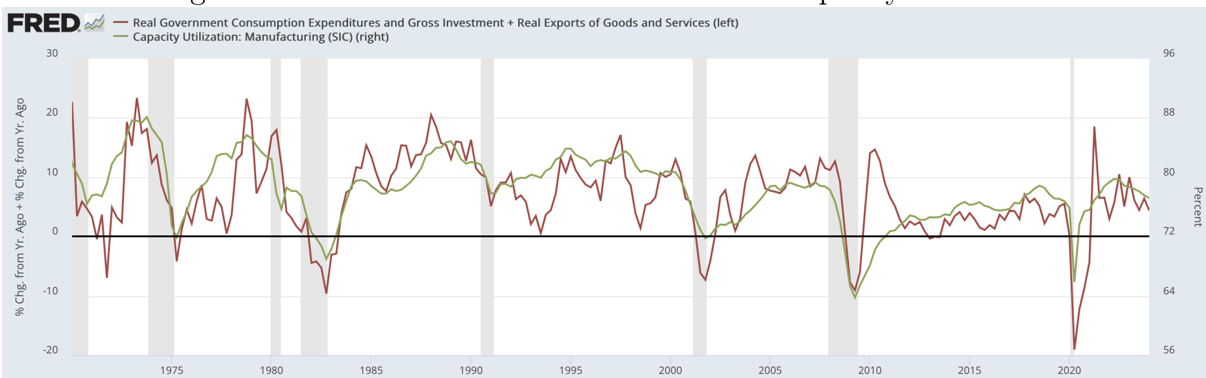
Fig. 1. Labour Productivity in the US (1970-2024)



Source: Own elaboration based on data provided in Appendix A.

Another key stylized fact is that the growth rate of autonomous demand – specifically represented here by real government consumption and real exports – shows a strong correlation with the level of capacity utilization (see Figure 2). This relationship highlights how changes in autonomous demand significantly impact the extent to which productive capacity is utilized, providing insights into the dynamics of economic activity within the economy.

Fig. 2. Growth of Autonomous Demand and Capacity Utilization



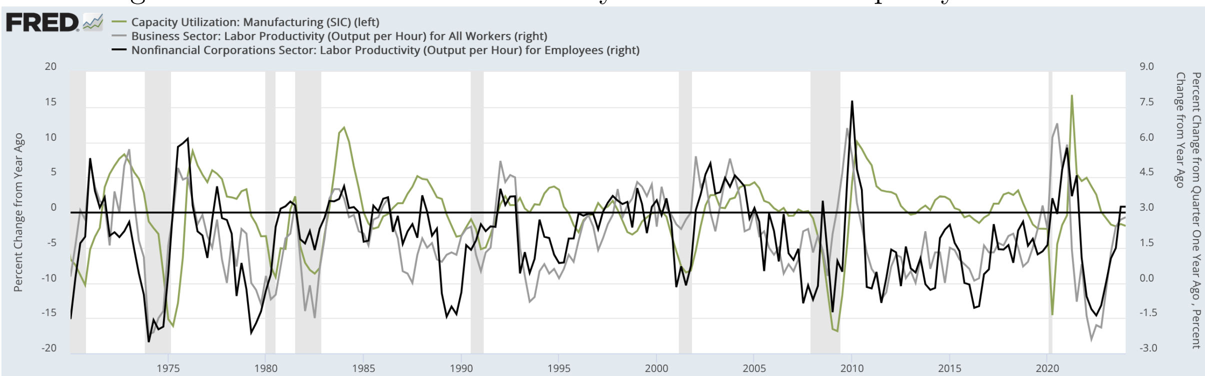
Source: Own elaboration based on data provided in Appendix A.

What are the implications when we combine these two stylized facts? Although the relationship between the level of capacity utilization and the productivity growth rate might not be immediately evident when analyzed separately (as illustrated in Figure 3), a clearer picture emerges when we examine the productivity growth rate in conjunction with the growth rate of capacity utilization (see Figure 4). By analyzing these two variables together, we can gain a more nuanced understanding of how changes in productivity and capacity utilization are interconnected.

Fig. 3. Growth of Labor Productivity and Level of Capacity Utilization

Source: Own elaboration based on data provided in Appendix A.

Fig. 4. Growth of Labor Productivity and Growth of Capacity Utilization



Source: Own elaboration based on data provided in Appendix A.

From a Sraffian perspective, these stylized facts can be explained as follows: an impulse, such as an increase in the level of autonomous demand, leads to higher capacity utilization and an expansion in production levels. This rise in production prompts entrepreneurs to invest in *new* machinery, which is at the cutting edge of technological advancement. According to Cesaratto, Serrano, and Stirati (2003), this process of induced investment in new technology eventually boosts output per hour worked. Innovations typically reduce the total labor requirements needed per unit of aggregate output, enhancing productivity. More broadly, technical progress generally decreases the amount of labor required to produce the same level of output (Garegnani, 2015, p. 14, fn. 28).

Cesaratto et al. (2003) argue that historical evidence supports the notion that a rapid increase in aggregate demand allows for a greater number of inventions to transition into innovations, thereby accelerating the growth of output per worker. This rapid growth in productivity can be partially attributed to factors such as increasing returns and learning-by-doing effects, which indicate a significant endogenous component in productivity growth. Economic expansion fosters a more refined division of labor, aligns with Adam Smith's ideas on specialization, facilitates the introduction of new products, and stimulates innovative activities. This, in turn, helps to speed up the recovery of costs associated with innovations before they are widely replicated (Cesaratto, 1996).

3.2. Data and Identification Strategy

So, how can we effectively synthesize all these stylized facts? The aim of this section is to analyze and understand how labor productivity in the United States has reacted to increases in autonomous demand over the specified period (1970Q1-2024Q2). When referring to autonomous demand (LAD), we are specifically looking at components such as public expenditure (real government consumption) and real exports. By investigating these elements, we seek to uncover the relationship between shifts in autonomous demand and changes in labor productivity. This analysis will provide insights into how variations in public spending and export levels impact productivity growth, offering a comprehensive understanding of the interplay between these economic factors and productivity trends throughout the observed timeframe.

Table 2: The Sraffian Supermultiplier (SSM) and Technical Change (TC): 6 empirical tests

	Type of TC
Model 1	1.1. Exogenous TC
Model 1	1.2. Endogenous TC
Model 1	1.3. TC as a Control
Model 2	2.1. Exogenous TC
Model 2	2.2. Endogenous TC
Model 2	2.3. TC as a Control

Source: Own elaboration.

The estimation will be conducted using a Structural Vector Autoregression (SVAR) (Cholesky Identification). We will analyze impacts on our 'exogenous' variable of interest (Autonomous Demand) concerning labor productivity, capacity utilization, inflation, and productive capacity (Model 1). Within Model 1, we will examine 3 variations: one with exogenous TC, one with endogenous TC, and one with TC as a control variable. In Model 2, we will analyze impacts on our exogenous variable (Autonomous Demand) concerning labor productivity, unemployment rate, inflation, and labor force participation. Similarly to the previous case, within Model 2, we will explore 3 variations: one with exogenous technological change, one with endogenous technological change, and one with technological change as a control (see Table 2). We will analyze 6 empirical models.

3.3. Autonomous Demand and Technical Change: some results

In this section, we will develop 6 models: 1.1., 1.2., 1.3., 2.1., 2.2., and 2.3..[1] The order of variables (arranged from most 'exogenous' to most 'endogenous') will be as indicated in Table 3.

[1] At the FMM conference, we will only present models 1.1, 1.2, 2.1, and 2.2.

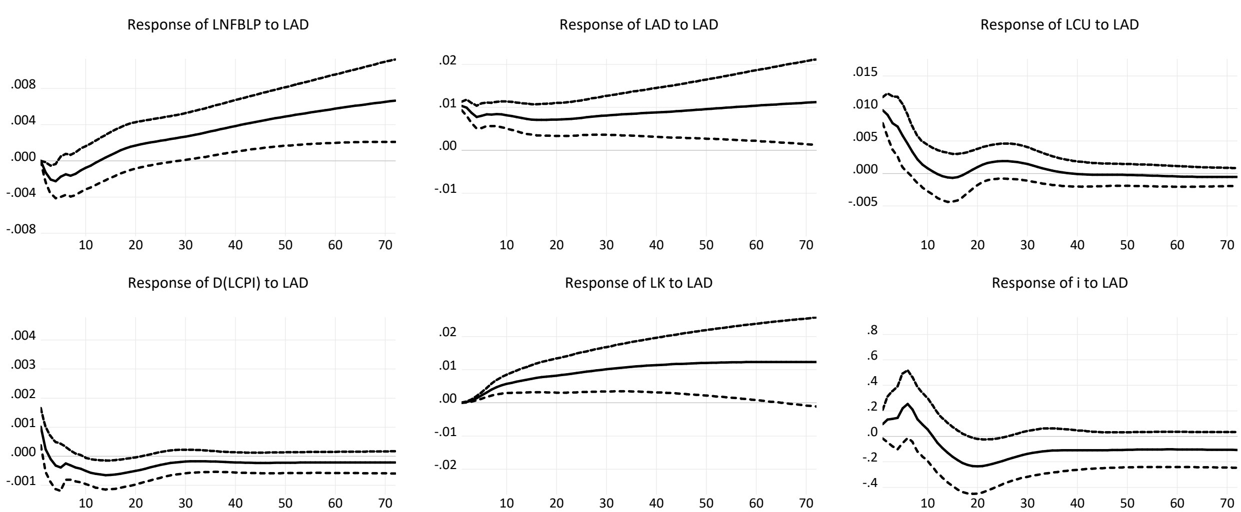
Table 3: Order of Variables in SVAR: Model 3 and Model 4

Model 1.1.	$LP \to AD \to CU \to \pi \to K$
Model 1.2.	$AD \to LP \to CU \to \pi \to K$
Model 1.3.	$AD \to CU \to \pi \to K$
Model 2.1.	$LP \to AD \to U \to \pi \to LFPR$
Model 2.2.	$AD \to LP \to U \to \pi \to LFPR$
Model 2.3.	$AD \to U \to \pi \to LFPR$

Source: Own elaboration.

For example, in Model 1.1., we consider labor productivity ($LNFBP$) as the most exogenous variable, followed by autonomous demand (LAD), capacity utilization (LCU), inflation (π), and productive capacity (LK). In Model 1.2., only the order between autonomous demand (LAD) and labor productivity ($LNFBP$) changes. In Model 1.3., labor productivity ($LNFBP$) appears as a control variable. The same applies to Model 2 (2.1., 2.2., 2.3.), in which we analyze the unemployment rate (LU) and the labor force participation rate ($LLFPR$). In all our models we controlled for the interest rate which was put at the end of all equations as the most endogenous.

Fig. 5. Model 1.1.

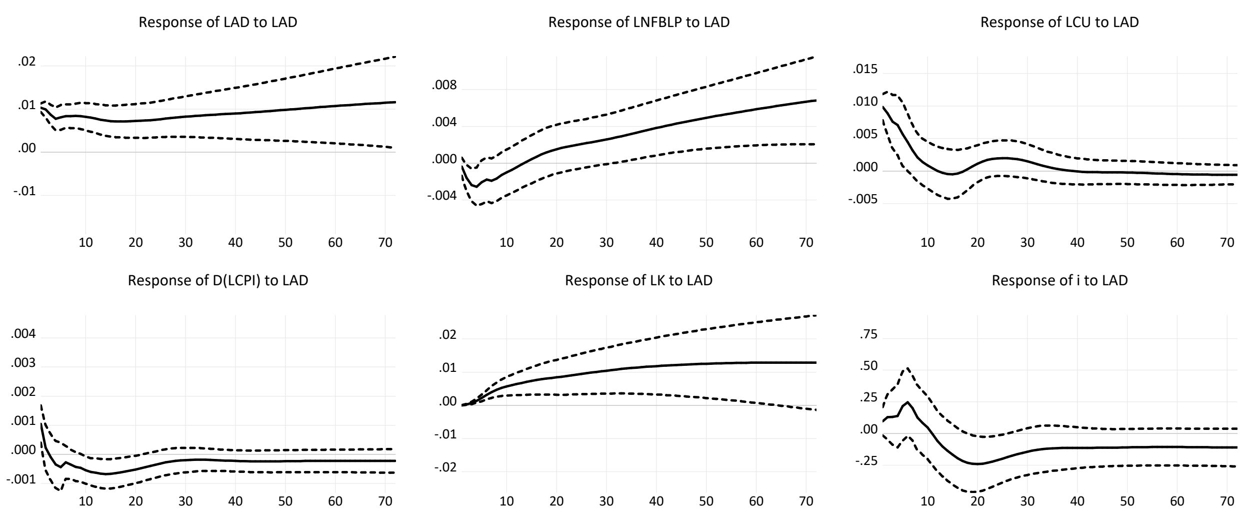


Source: Own elaboration based on data provided in Appendix A.

In Figure 5, we present the detailed results of Model 1.1. In this particular scenario, even though labor productivity is considered more exogenous, what we observe in the figures is the comprehensive impact of autonomous demand (LAD) on various key variables such as labor productivity ($LNFBLP$), autonomous demand itself (LAD), the utilization rate of industrial installed capacity (LCU), inflation ($D(LCPI)$), industrial productive capacity (LK), and also on the interest rate (i), which is treated as a control variable within the model. These interactions highlight the intricate dynamics between these variables.

The findings indicate that a sustained increase in autonomous demand, persisting over **72 quarters**, leads to a long-term increase in labor productivity and industrial productive capacity. This effect underscores the significant influence of autonomous demand on these factors over time. Meanwhile, the impacts on the utilization of industrial installed capacity and inflation are notably transitory, suggesting that while they do respond to shifts in autonomous demand, these effects diminish over time, stabilizing at their original levels.

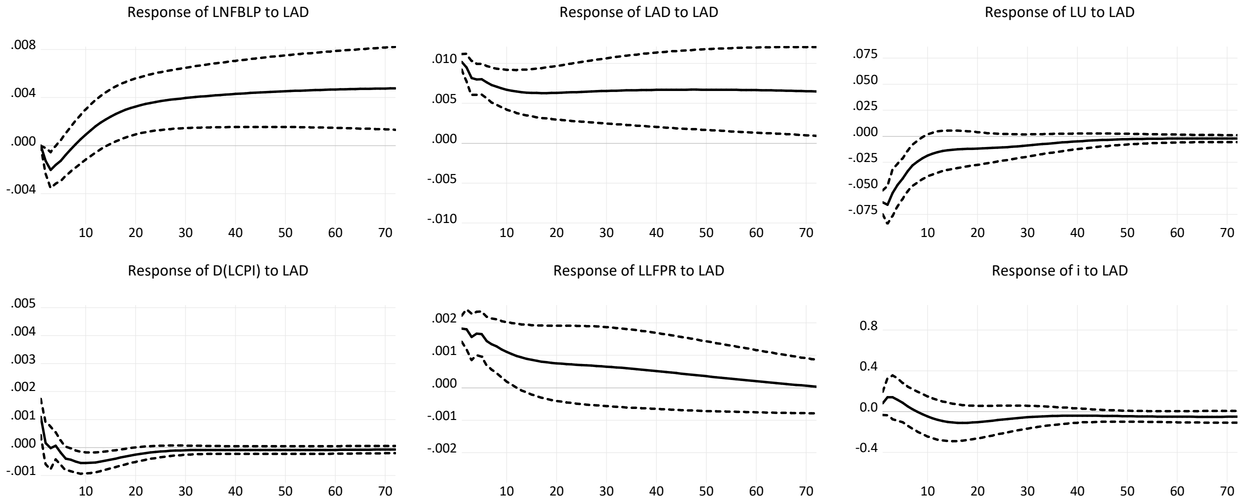
Fig. 6. Model 1.2.



Source: Own elaboration based on data provided in Appendix A.

Similar outcomes are observed in Model 1.2, where the ordering of the variables is slightly modified (see Table 3 for reference). In this scenario, despite the slight differences in variable ordering, the results remain almost identical, reinforcing the robustness of the observed relationships across different specifications of the model.

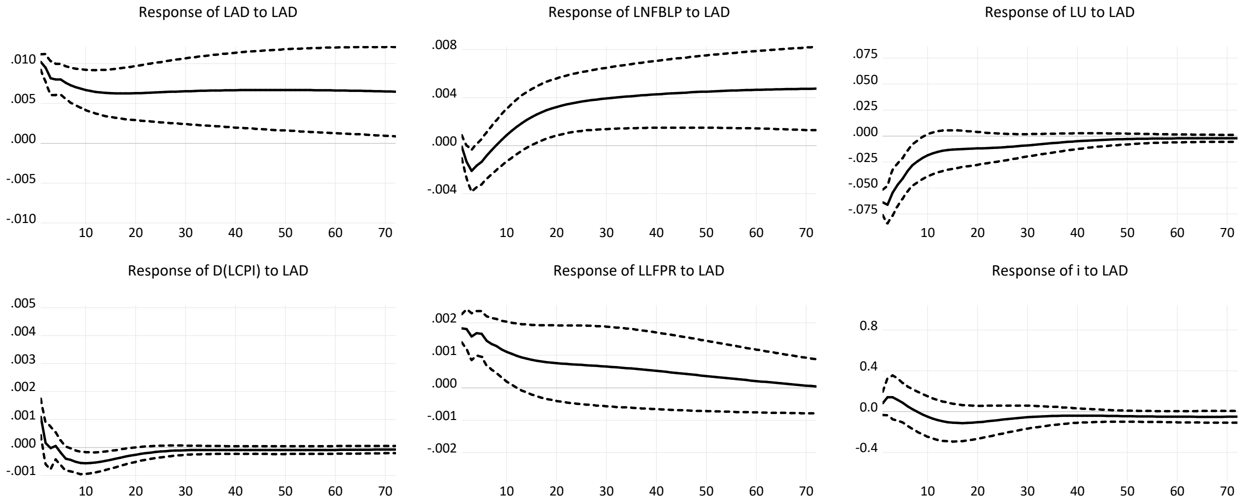
Fig. 7. Model 2.1.



Source: Own elaboration based on data provided in Appendix A.

In Model 2.1, our focus shifts towards examining the labor 'market'. Within this model, we analyze how an increase in autonomous demand exerts a permanent effect on labor productivity. Additionally, it generates transitory effects on unemployment, inflation, and the labor force participation rate. These findings provide valuable insights into how demand-side dynamics can shape labor market outcomes, influencing both long-term productivity and short-term labor market conditions. This further emphasizes the critical role of autonomous demand in shaping broader economic trends across multiple domains. Similar outcomes are observed in Model 2.2, where the ordering of the variables is slightly modified (see Table 3 for reference).

Fig. 8. Model 2.2.



Source: Own elaboration based on data provided in Appendix A.

4. Conclusions

The conclusions of this work highlight the central role of autonomous aggregate demand in driving long-term economic outcomes, aligning with Keynesian theories that emphasize demand-side factors in determining production, employment, and productive capacity. Our analysis demonstrates that autonomous demand is not merely a short-term influence but a critical component in shaping the broader trajectory of the economy over time.

Key findings suggest that sustained changes in autonomous demand have a profound and lasting impact on key variables such as labor productivity and productive capacity. This underscores the importance of policies aimed at stimulating autonomous demand as a means to foster long-term economic growth and employment. Moreover, the observed transitory effects on variables like capacity utilization and inflation highlight the nuanced ways in which demand influences the economy, with some effects being more persistent than others.

The robustness of these results across different model specifications reaffirms the reliability of the relationships between autonomous demand and economic performance. Even with variations in model setups and econometric techniques, the consistent findings suggest that the influence of autonomous demand transcends specific conditions or configurations, reinforcing its significance in economic analysis.

Overall, the study underscores that autonomous aggregate demand plays a vital role in driving both short-term adjustments and long-term economic growth. Policymakers should consider the powerful implications of autonomous demand in designing strategies that aim not only to stabilize the economy in the short run but also to enhance its productive potential over the long term. This perspective aligns with Keynesian thought, which advocates for a demand-driven approach to achieving sustained economic prosperity.

5. References

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Appendix A. Data sources

- Nonfarm Business Sector: Labor Productivity (Output per Hour) for All Workers (OPHNFB) U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Labor Productivity (Output per Hour) for All Workers [OPHNFB], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OPHNFB, July 12, 2024.

- Autonomous Demand (LAD). Government Consumption plus Exports. Variable in logarithms. Real Government Consumption Expenditures, U.S. Bureau of Economic Analysis, Real Government Consumption Expenditures [A955RX1Q020SBEA], retrieved from FRED, Federal Reserve Bank St. Louis; `https://fred.stlouisfed.org/series/A955RX1Q020SBEA`, July 12, 2024. Plus Exports. U.S. Bureau of Economic Analysis, Real Exports of Goods and Services [EXPGSC1], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/EXPGSC1`, July 12, 2024.

- Capacity utilization (LCU). Board of Governors of the Federal Reserve System (US), Capacity Utilization: Manufacturing (SIC) [CUMFNS], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/CUMFNS`, July 12, 2024. Variable in logarithms.

- Consumer Price Index ($LCPI$). U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/CPIAUCSL`, July 12, 2024.

- Industrial capacity (LK). Board of Governors of the Federal Reserve System (US), Industrial Capacity: Manufacturing (SIC) [CAPB00004SQ], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/CAPB00004SQ`, July 12, 2024. Variable in logarithms.

- Labor Force Participation Rate ($LLFPR$). U.S. Bureau of Labor Statistics, Labor Force Participation Rate [CIVPART], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/CIVPART`, July 12, 2024.

- Unemployment Rate (LUR). U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/UNRATE`, July 12, 2024. Variable in logarithms.

- Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate [FEDFUNDS], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/FEDFUNDS`, July 12, 2024.

Appendix B. Model Selection Criteria

Table 4: Model 1: VAR Lag Order Selection Criteria

Lag	AIC	Obs
0	-11.58	212
1	-33.20	212
2	-35.42	212
3	-36.82	212
4	-37.85	212
5	**-37.96***	**212**

Source: own computations based on data provided.

Table 5: Model 2: VAR Lag Order Selection Criteria

Lag	AIC	Obs
0	-10.32	212
1	-30.12	212
2	-30.15	212
3	**-30.23***	**212**
4	-30.09	212
5	-29.96	212

Source: own computations based on data provided.

Appendix C. On the exogeneity of autonomous demand: a Granger-causality test

Granger (1969) proposes a statistical method to test for causality between two variables, focusing on their feedback mechanisms by assessing temporal precedence. While this method does not serve as a substitute for causality in the theoretical sense, it provides an additional aspect to consider when we assert in the article that autonomous demand is 'exogenous' to GDP. This statistical approach helps to reinforce the distinction between correlation and causation by examining whether past values of one variable can predict the future values of another, thereby offering insights into the directional influence between the variables in question. Thus, Granger causality analysis can be a valuable tool in empirical research to support arguments about the exogeneity of autonomous demand in relation to GDP, even though it doesn't establish true causality in a philosophical or theoretical framework. Because series are nonstationary, in order to apply a Granger causality test, we applied the Toda and Yamamoto (1995) procedure, hence with five lags (in levels and in growth rates).

Table 6: Granger Causality Test

Null Hypothesis	ADF	Obs
LGDP does not Granger Cause LAD	2.68**	213
LAD does not Granger Cause LGDP	3.81***	213
D(LGDP) does not Granger Cause D(LAD)	0.95	212
D(LAD) does not Granger Cause D(LGDP)	3.57***	212

Note: *=pval<0.1, **=pval<0.05, ***=pval<0.01.

Source: own computations based on data provided.

Table 5 illustrates causality in the Granger sense. In the model using levels, we can reject the hypothesis that GDP does not cause autonomous demand and vice versa, as the null hypothesis is rejected at the 1% confidence level. This suggests a bidirectional causal relationship between GDP and autonomous demand when considering levels. However, when examining the variables in terms of their growth rates, the results differ: we cannot reject the null hypothesis that GDP growth does not cause growth in autonomous demand, indicating no significant causality from GDP growth to autonomous demand growth. Conversely, we can reject the hypothesis that the growth rate of autonomous demand does not cause the growth rate of GDP, also at a 1% confidence level, indicating a significant unidirectional causality from autonomous demand growth to GDP growth.

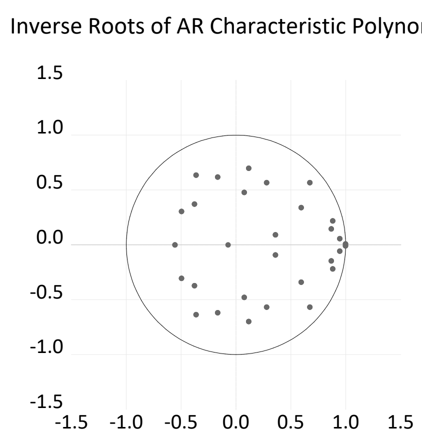
In summary, while there is evidence of a feedback effect when analyzing the variables in levels, the Granger causality tests using growth rates support the notion that autonomous demand growth significantly influences GDP growth. This reinforces the view that autonomous demand plays an exogenous role in driving GDP growth, underscoring its importance as an independent driver rather than merely a response to GDP changes. Thus, the findings support the idea that autonomous demand can be seen as a leading indicator or driver of economic growth in terms of GDP, particularly when growth rates are considered.

Appendix D. Stability Conditions, Residual Diagnostics

D.1. *Inverse Roots of AR Characteristic Polynomial*

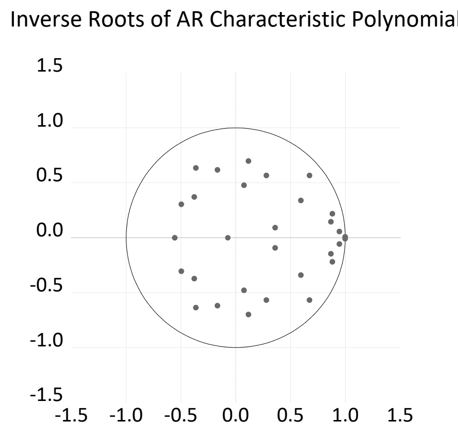
All the inverse roots of the characteristic AR polynomial have moduli less than one and are located within the unit circle, indicating that the estimated VARs are stable (see Figure 9, 10, 11 and 12). Additionally, when examining the autocorrelations across all models, it is observed that the autocorrelations of all variables (measured at 12 lags) do not exceed the 2 standard error bounds. Detailed tables and graphs illustrating these findings are available upon request.

Fig. 9. Model 1.1.



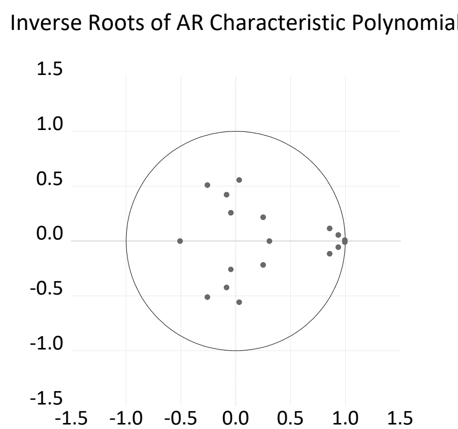
Source: Own elaboration based on data provided in Appendix A.

Fig. 10. Model 1.2.



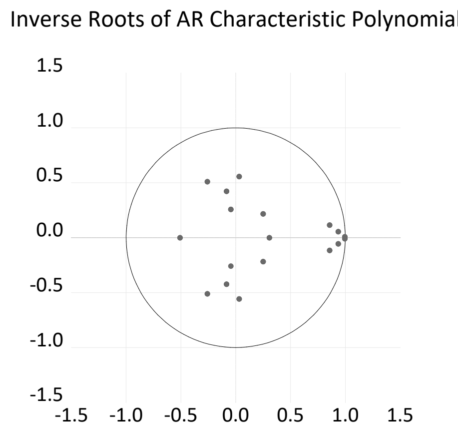
Source: Own elaboration based on data provided in Appendix A.

Fig. 11. Model 2.1.



Source: Own elaboration based on data provided in Appendix A.

Fig. 12. Model 2.2.



Source: Own elaboration based on data provided in Appendix A.

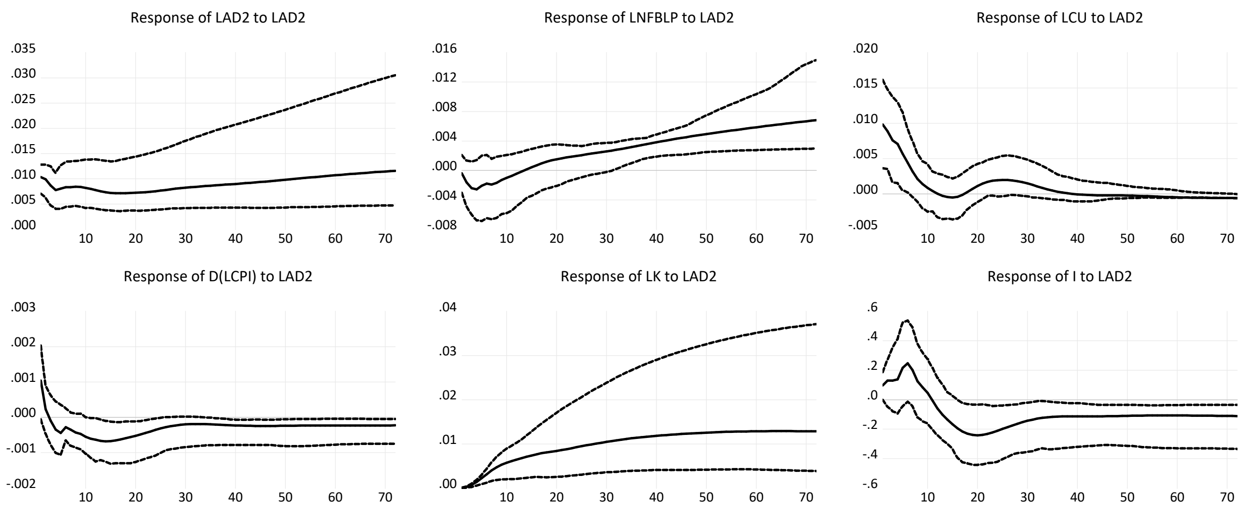
D.2. Autocorrelation

Furthermore, the analysis of autocorrelations through LM tests – conducted with 5 lags for Model 1 and 3 lags for Model 2, respectively – also shows no evidence of autocorrelation issues in the developed models. These results are available upon request. This comprehensive assessment confirms the robustness of the models, as the absence of significant autocorrelations supports the validity of the estimations and the reliability of the model specifications.

D.3. Bias and Skewness

To ensure that the results of our model are not affected by bias and skewness, we present and analyze the outcomes by applying the bootstrap method developed by Kilian in 1998. This approach helps in providing more robust and reliable statistical estimates by repeatedly resampling the data. By using Kilian's bootstrap technique, we can mitigate the influence of outliers and non-normality in the data, thereby enhancing the credibility and validity of our findings. Therefore, we have decided to report the findings by employing the bootstrap approach as proposed by Kilian (1998). Specifically, we used a confidence interval of 0.95, encompassing 200 single bootstrap replications and 100 double bootstrap replications to ensure robustness and reliability of the results. This method allows for a more accurate reflection of variability within our data, addressing potential biases caused by heteroscedasticity and providing a more nuanced understanding of the underlying statistical properties. The results derived from this bootstrap technique should be interpreted as a robust estimation that accommodates the irregular variances in the error terms, reinforcing the validity of our analytical outcomes. For reasons of space, we present here the 1.2. model, but all other models are available upon request.

Fig. 13. Bootstrap: Model 1.2.



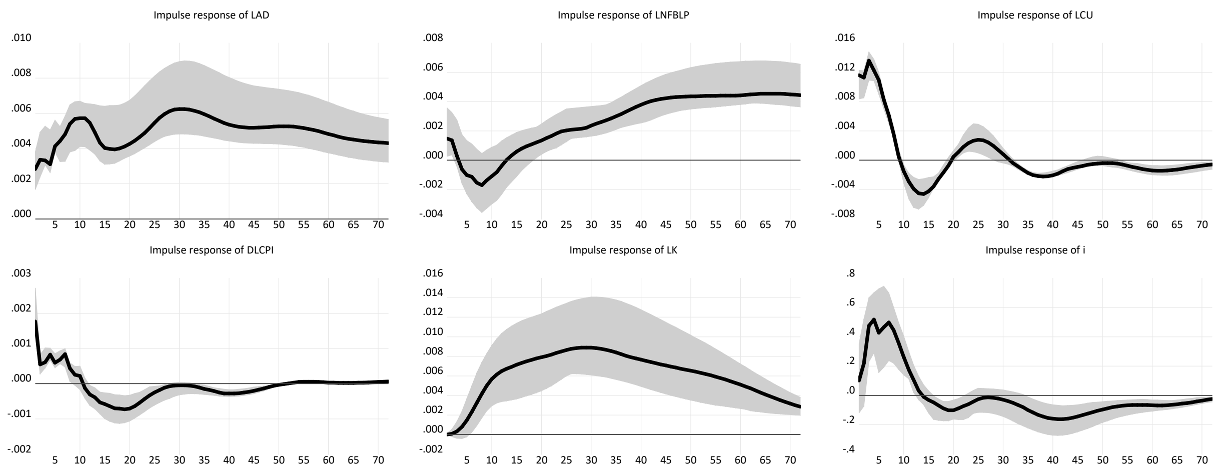
Source: Own elaboration based on data provided in Appendix A.

It is interesting to note how here the effect of autonomous demand can be deflationary in the long run (economies of scale that reduce production costs).

Appendix E. Robustness: An agnostic identification procedure

Sign restriction models (SR) have emerged as an alternative to the traditional Cholesky decomposition approach in Structural Vector Autoregressive (SVAR) models. Cholesky decomposition requires the imposition of a specific ordering of variables, which can be quite restrictive and may not always reflect the true causal relationships in the data. This ordering can significantly impact the results and interpretations of the model. Uhlig (2005) provides a comprehensive overview of sign restriction models, demonstrating their ability to avoid the pitfalls of ordering assumptions by using sign constraints to identify policy shocks. SR models use information about the expected direction of the effects of shocks, which can be derived from economic theory or empirical evidence. This approach might provide more flexibility and can lead to more accurate and reliable estimates of structural responses. Moreover, SR models might reduce the sensitivity of the results to specific model specifications and might help to ensure that the findings are more robust and less dependent on arbitrary choices. 68 per cent.

Fig. 14. Sign Restriction: Model 1.2.



Source: Own elaboration based on data provided in Appendix A.

In this case, we include 3 sign restrictions. Positive on autonomous demand, positive on capacity utilisation and positive on inflation.[2] The results, with a 68% confidence intervals, are almost the same as those obtained with the bootstrap and the traditional SVAR.

[2]From a classical-Keynesian point of view, as there is an analytical separation between prices and quantities, it is not possible to determine general rules between these aggregates in the long run. For example, an increase in aggregate demand may influence the scale of production and may reduce unit costs; in this case we would have an increase in aggregate demand and a negative impact on the price level. The recognition of the positive shock on inflation is undertaken to show that even with a shock identification in line with more marginalist/neoclassical works, the impact of autonomous demand seems to play a role on productive capacity and labour productivity in the long run.