Autonomous and induced demand in the United States between 1960-2019: A long-run approach

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Abstract:
This paper presents a long-run study of the relationship between autonomous and induced demand spanning 1960–2019 for the United States. Our exercise can be considered a contribution to the burgeoning empirical literature revolving around autonomous demand-led growth models, which have displayed the potential to establish bridges not only within the Post-Keynesian community, but also between Post-Keynesian economics and other evolutionary and pluralistic approaches to economic growth. In particular, we study the long-run dynamic relationship between autonomous demand - which comprises R&D expenditures, government spending, exports and residential investment - and induced demand. Through a cointegration model with quantile-varying coefficients, we account for the possibility of changes in the relationship between the two variables of interest and demonstrate that the long-run equilibrium relationship between autonomous and induced demand is robust to exogenous shocks and changes in the parameters.

Keywords: autonomous demand; induced demand; autonomous demand-led growth; supermultiplier; accounting identity

1. INTRODUCTION

The principle of effective demand, brought to the forefront by the works of Keynes and Kalecki, postulates that demand generates its own supply, without being constrained by the latter. A corollary of the principle of effective demand is that aggregate demand can be split between an autonomous part, independent or at least not mechanically linked to the level of output/income, and an induced part, whose evolution is driven by that of output/income. The focus of this work will be exactly on the dynamic relationship between autonomous and induced demand.

Our exercise can be considered a contribution to the burgeoning empirical literature revolving around autonomous demand-led growth models, which are gaining increasing popularity in the Post-Keynesian scientific community. The main implication of these models, whose first example is the supermultiplier model of Serrano (1995) and Freitas & Serrano (2015), is that autonomous demand drives output in the long run, in a theoretical context where private capacity-creating investment is treated as a component of the induced part of demand (Pérez-Montiel & Manera, 2020).
Stimulated by the supermultiplier’s capacity to generate a stable path in which demand, production and productive capacity grow in step, a series of recent works has also explored the possibility of extending this model to include features from supply-side approaches to growth. For example, Nomaler et al. (2021) develop a supermultiplier model in which supply-side parameters related to research and development (R&D) and technical change determine growth. Allain (2019, 2021) semi-endogenizes autonomous demand by introducing a feedback effect from the employment rate to the average propensity to consume, while Nomaler et al. (2020, 2022), Deleidi & Mazzucato (2019, 2021) and Di Domenico & Russo (2022) connect it to the neo-Schumpeterian tradition. Hence, the compatibility of supermultiplier models with different approaches to growth highlights its potential to establish bridges not only within the narrow Post-Keynesian community, but also between Post-Keynesian economics and other evolutionary and pluralistic approaches to economic growth.

Independently of the functioning of the process through which demand (both autonomous and induced) and supply adjust to each other to produce a meaningful and stable steady state growth path, the supermultiplier model states that the level of economic activity (GDP) equals the product of the supermultiplier and autonomous demand and that the latter drives growth in the long run. While several authors have already tried to assess the empirical plausibility of this theoretical result, this has been mostly done by providing evidence of cointegration between autonomous demand and output (Médici, 2011; Girardi & Pariboni, 2016; Perez-Montiel & Erbina, 2020; Haluska et al., 2021).¹ We argue, however, that autonomous demand and output might be cointegrated by national accounting construction, because autonomous demand is a component of Gross Domestic Product. This might lead to a bias in favor of a correlation between these two variables, whatever real causal relationships may exist between them (Michaely 1977).

¹ For discussions about the theoretical consistency and empirical relevance of supermultiplier models, see also Pariboni (2016), Portella-Carbó (2016), Dejuán (2017), Hein (2018), Portella-Carbó & Dejuán (2019). It is important to notice that, in recent years, also authors coming from a Kaleckian theoretical tradition have developed analytical models whose main implications are analogous to those of the supermultiplier. See, e.g., Allain (2015), Lavoie (2016, 2017), Hein (2018) and Fiebiger & Lavoie (2019).
For this reason, we adopt a different strategy and investigate the dynamic equilibrium relationship between autonomous and induced demand. In particular, we assess whether autonomous and induced demand are cointegrated. This poses, however, a preliminary challenge: which component of demand falls in the first category and which one in the other? The issue is not trivial, and a theoretically informed choice is in order, as it will be discussed in the next section.

For our empirical purposes, we use a quantile cointegration test to consider the possibility of a non-linear dynamic equilibrium relationship between autonomous and induced demand. This approach is robust to asymmetries, nonlinearities and structural breaks in the relationship between the two variables. To the best of our knowledge, this is the first attempt to empirically address the issues under discussion through a quantile cointegration method.

The paper proceeds as follows. In Section 2 we briefly discuss the autonomous vs induced demand dichotomy and expose the supermultiplier approach to economic growth. Section 3 and 4 describe, respectively, our identification strategy and the econometric methodology employed. Section 5 presents and discusses the results, while the last section concludes.

2. AUTONOMOUS DEMAND AND INDUCED DEMAND

As already said, induced demand is influenced by the level of income and production. Household consumption, or at least a part\(^2\) of it, is then the most likely candidate to be labeled as such, being funded out of wages or profits. We also include in induced demand, and in doing this we distance ourselves from the original Keynesian insight, also private, capacity-creating non-residential investment. While the latter is not necessarily funded by (current or past) income, it still depends on the evolution of demand and is systematically related to the production requirements: capitalists invest to make production meet expected demand. Thus, investment follows the capital stock adjustment principle, so that permanent increases in demand and production induce the expansion of productive capacity.

\(^2\) The other part is financed out of debt or accumulated wealth.
Our choice, hence, reflects the definition of autonomous demand, proposed by Serrano, as *all those expenditures that are not financed by wage income generated by production decisions, nor affect (directly) the productive capacity of the economy* (Serrano 1995). In the related growth literature, these expenditures usually comprise exports (see, e.g., Nah & Lavoie 2017 and Morlin, 2022), government spending (see, e.g., Allain, 2015; Hein & Woodgate, 2021 and Morlin, 2022) and that portion of household consumption that is either out of wealth or credit-financed (see, e.g., Pariboni, 2016, Lavoie, 2016, Hein & Woodgate, 2021, and Barbieri Góes & Deleidi, 2022).

A relatively less explored source of autonomous demand is constituted by R&D expenditures. These expenditures do not add to the productive capacity of the economy but rather contribute to its transformation, being a vector of technical progress. Moreover, they are not mechanically linked to the evolution of output or of demand but are the manifestation of the attempt by innovators to anticipate and dictate trends that would not manifest themselves without these research and development efforts, representing in this way a litmus test for a society’s dynamism. Caminati & Sordi (2019) and Nomaler et al. (2021) theoretically explore the role of R&D in the context of an autonomous demand-led growth model. At the empirical level, in the same framework, the task is accomplished by Gallo (2019) and Haluska et al. (2021).

As it is very well-known, the relationship between autonomous and induced demand crystallizes in the multiplier and its components (Nomaler et al., 2021: 1). When, following among others Harrod (1939) and Samuelson (1939), investment is made endogenous to output through an accelerator mechanism, the multiplier becomes larger, *ceteris paribus*, as compared to the simple Keynesian model where investment is exogenous in the short run. This larger multiplier was labeled by Hicks (1950) as the

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3 See also Cesaratto et al. (2003); Freitas & Serrano (2015); Girardi & Pariboni (2016, 2020); Pérez Caldentey & Vernengo (2017); Palley (2019), where similar conceptualizations are adopted.

4 The interested reader can also refer to Girardi & Pariboni (2016, 2020); and Perez-Montiel & Erbina (2020), for a broader discussion about the rationale of including these demand components in autonomous demand.

5 There is, however, a relevant difference between the work by Nomaler et al. (2021) and ours. In the former, the authors focus on the supply-side determinants of R&D, while we emphasize its demand-side nature, as an act of spending and as a component of aggregate demand.

6 See also Deleidi & Mazzucato (2019, 2021). Consider, however, that in these works the demand component under the spotlight is public mission-oriented innovation spending, a concept more specific than and only partially superimposable to (public) R&D.
Supermultiplier. Starting from the nineties, the supermultiplier concept, that is to say a multiplier cum accelerator, has been rediscovered by a group of Classical-Keynesian economists (Serrano, 1995; Bortis, 1997; Dejuan, 2005), followers of the tradition initiated by Garegnani (1978).

Albeit this is often not the main focus of these contributions, it is understood that the relationship between autonomous and induced demand, as postulated by the (super)multiplier, is subject to change and could vary over time for a multiplicity of reasons, such as shifts in income distribution affecting the aggregate propensity to consume, technical progress altering the capital requirements and, hence, the investment function, changes in tastes and patterns of consumption contributing to a higher or lower relevance of imports, and so on and so forth. This is why we enrich our empirical investigation with a quantile cointegration analysis, as it will be detailed in section 4.2.

3. IDENTIFICATION STRATEGY

Several investigations have provided evidence of a long-run equilibrium relationship between output and autonomous demand (see, e.g., Médici, 2011; Girardi & Pariboni, 2016; Perez-Montiel & Erbina, 2020; Haluska et al., 2021). This is in line with the main postulate of the supermultiplier model. However, since autonomous demand \((Z_t \text{ thereafter})\) is a component of aggregate demand and output (\(GDP_t \text{ thereafter}\)), testing the long-run relationship between \(GDP_t\) and \(Z_t\) might carry problems related to national accounting identity. In other words, \(GDP_t\) and \(Z_t\) might be cointegrated by national accounting construction.

For instance, it has been shown that, within the exports led-growth literature, it is problematic that exports – via the national accounting identity – are themselves a component of output (Michaely 1977). To solve this, we must separate the ‘economic influence’ of \(Z_t\) on output from the influence incorporated into the ‘growth accounting relationship’. To do so, following Michaely (1977) and Heller & Porter (1978), we proceed as follows: a Keynesian model in the spirit of the supermultiplier approach, briefly recalled in the previous section, states that in its long-run equilibrium position \(GDP_t\) equals \(Z_t\) multiplied by the value of the supermultiplier (SM), i.e., \(GDP_t = SM \cdot Z_t\).  

5
On the other hand, we also know that \( GDP_t = Z_t + ID_t \) (were \( ID_t = C_t + I_t \), is induced demand in period t, being \( C_t \) induced consumption and \( I_t \) induced capacity creating investment). Thus, \( GDP_t \) can also be represented as a function of \( ID_t \) and \( Z_t \):

\[
GDP_t \equiv Z_t + ID_t = SM \cdot Z_t,
\]

and, hence:

\[
ID_t = (SM - 1)Z_t,
\]

If the value of \( SM \) remains stable, there might be a cointegration relationship between \( ID_t \) and \( Z_t \). If these two variables follow an equilibrium relationship in the long-run, then the evidence in favor the postulates of the supermultiplier is free of any national accounting construction. Note also that the cointegration relationship could be nonlinear if \( SM \) is not constant. In the following sections we check for the existence of cointegration between \( ID_t \) and \( Z_t \).

4. DATA AND ECONOMETRIC METHODOLOGY

4.1. DATA

We employ Federal Reserve’s quarterly series between 1960:Q1 and 2019:Q2 for the United States. To consider autonomous demand as a whole, we follow the methodology introduced by Girardi & Pariboni (2016). According to Serrano (1995), autonomous demand is constituted by expenditures that do not generate productive capacity and whose evolution is not mechanically linked to the evolution of output (Serrano, 1995; Cesaratto et al., 2003; Freitas & Serrano, 2015; Girardi & Pariboni, 2016, 2020; Pérez Caldentey & Vernengo, 2017; Palley, 2019).

As discussed in section 2, we consider as potential elements of in autonomous demand Government spending, that is to say, Government consumption plus government investment (G), Residential Investment (RES), Exports (E), and Research & Development investment expenditure (R&D), for which an empirical counterpart is retrievable in a straightforward way. The task of splitting total household consumption in an induced and in an autonomous component is more complicated, to say the least, also in the light of the very likely endogeneity with respect to income of consumer credit.
For this reason, in line with Girardi & Pariboni (2016, 2020), Girardi et al. (2020), Pérez-Montiel & Erbina (2020), and Pérez-Montiel & Manera (2022), we only include in Z, as a part of autonomous consumption, the purchase of new houses (RES).  

Thus, we construct a proxy variable of autonomous demand as a whole by creating $Z_t = R&Di_t + RES_t + E_t + G_t$. On the other hand, to construct our dependent variable, induced demand ($ID_t$), we use the gross domestic product ($GDP_t$) minus autonomous demand ($Z_t$) in period $t$, thereby creating $ID_t = GDP_t - Z_t$. We work with the variables $ID_t$ and $Z_t$ in real terms (measured in billions of chained 2012 dollars, seasonally adjusted annual rate). Figure 1 plots the evolution of $ID_t$ and $Z_t$, and suggests that the variables evolve in step.

Figure 1. Autonomous demand ($Z_t$) and induced demand ($ID_t$) in the US.

Source: Federal Reserve. Variables measured in billions of chained 2012 dollars, seasonally adjusted annual rate.

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We are aware that, for national accounting purposes, this demand component is included in investment, even though its nature is more akin to the purchase of a durable consumption good. See Pérez-Montiel & Pariboni (2022) for an empirical investigation of the role of residential investment as an autonomous growth driver in the US.
4.2. QUANTILE COINTEGRATION ANALYSIS

In contrast to traditional linear cointegration models, several researchers suggest that the cointegrating vector between macroeconomic variables might not be constant (Lee and Zeng 2011). Actually, dependence and predictability across macroeconomic variables may be state-dependent, implying that the sign and significance of the involved dynamic relationships may be different above and below the average (Marques & Lima, 2022: 2). Thus, the cointegrating relationship between macroeconomic variables might change over the distribution, i.e., it might be time-varying. To deal with it, we apply the quantile cointegration test proposed by Xiao (2009) to check whether there is a long-run equilibrium relationship between \( ID_t \) and \( Z_t \). The quantile cointegration approach is more suitable for our research than the Markov-Switching methods because it does not explicitly require to pre-specify and test for the number of regimes in the macroeconomic variables (see Jochmann & Koop, 2015 for a discussion).

The quantile cointegration model of Xiao (2009) can capture systematic influences of the conditioning variables on the location, scale, and shape of the conditional distribution of the response variable (Troster et al. 2018). Since the test of Xiao (2009) allows testing for cointegration and also estimating the cointegrating parameters at each point of the conditional distribution of the variables, it is, by definition, a time-varying approach to detect and estimate long-run relationships (Xiao 2009). Each point of the conditional distribution of a macroeconomic variable captures the phase of it: usually, lower, middle and higher quantiles are related to periods of bearish, normal and bullish market conditions, respectively (see Balcilar et al., 2018; Albulescu et al., 2020; Shafiullah et al., 2021).

The quantile cointegration test of Xiao (2009) requires the variables to be I(1) processes; thus, we first analyze the unit root properties of our variables of interest at each quantile of the conditional distribution considering the conditional mean. We use the quantile auto-regressive (QAR) unit root tests of Koenker & Xiao (2012) and Galvao (2009). Let \( y_t \) be a discrete time stochastic process and let \( I_t^y := (y_{t-1}, \ldots, y_{t-s})' \in \mathbb{R}^s \) denote the information set. Besides, \( F_y(\cdot | I_t^y) \) is the conditional distribution function of
\( y_t \) given \( I_t^\tau \), and thus we specify the following quantile linear regression model to perform the quantile autoregressive unit root test:

\[
Q^\tau(y_t | I_t^\tau) = \mu_1(\tau) + \mu_2(\tau)t + \alpha(\tau)y_{t-1} + \sum_{j=1}^{\bar{p}} \alpha_j(\tau) \Delta y_{t-j} + F_{e^{-1}}(\tau),
\]

where \( Q^\tau(y_t | I_t^\tau) \) is the \( \tau \)-quantile of \( F_{y_t \cdot \cdot I_t^\tau} \), \( \mu_1(\tau) \) is the drift term, \( t \) denotes the linear trend, \( \alpha(\tau) \) is the persistence parameter, and \( F_{e^{-1}}(\cdot) \) the inverse conditional distribution of the errors for each quantile. Then, a different persistence parameter \( \alpha \) for each quantile of the conditional distribution of \( y_t \) can be estimated. To test the null hypothesis \( H_0: \alpha(\tau) = 1 \), we apply the t-statistic proposed by Koenker & Xiao (2012) and Galvao (2009) at different quantiles \( \tau \in T \).

Next, we use the quantile cointegration test of Xiao (2009) to test for the long-run equilibrium relationship between ID\(_t\) and \( Z_t \). Thus, our initial proposed cointegrating equation is:

\[
ID_t = \alpha + \beta Z_t + \sum_{j=1}^{\bar{p}} \Pi_j ID_{t-j} + \sum_{j=1}^{\bar{q}} y_j Z_{t-j} + \varepsilon_t,
\]

where \( ID_t \) and \( Z_t \) are \( I(1) \) processes, and \( \varepsilon_t \) is stationary. To deal with endogeneity in standard cointegration models, Xiao (2009) follows Saikkonen (1991) and decomposes \( \varepsilon_t \) into lead-lag terms and a pure innovation component, \( e_t \), which is equivalent to the dynamic OLS estimator of Sims et al. (1990):

\[
ID_t = \alpha + \beta' Z_t + \sum_{j=1}^{\bar{K}} \Delta Z_{t-j} \Pi_j + e_t.
\]

Thus, the quantile analog is given by

\[
Q^\tau(ID_t | I_t^{ID}, I_t^Z) = \alpha(\tau) + \beta(\tau)' Z_t + \sum_{j=1}^{\bar{K}} \Delta Z_{t-j} \Pi_j + F_{e^{-1}}(\tau).
\]

The equation including a quadratic term of the regressor in the quantile cointegration is given by:

\[
Q^\tau(ID_t | I_t^{ID}, I_t^{Z^2}) = \alpha(\tau) + \beta(\tau)' Z_t + \gamma(\tau)' Z_t^2 + \sum_{j=1}^{\bar{K}} \Delta Z_{t-j} \Pi_j + \sum_{j=1}^{\bar{K}} \Delta Z_{t-j}^2 \Gamma_j + F_{e^{-1}}(\tau).
\]
The stability of the cointegrating coefficients in Equation (7) can be tested through the test statistic based on the supremum norm of the absolute value of the difference \( \bar{V}_n(\tau) = \hat{\beta}(\tau) - \bar{\beta} \) under the null hypothesis that \( \beta(\tau) = \beta \) over all quantiles. Thus, the test statistic \( \text{Sup}_\tau |\bar{V}_n(\tau)| \) over all quantiles of the distribution can be used. We performed 50000 Monte Carlo simulations to calculate the critical values of the test statistic \( \text{Sup}_\tau |\bar{V}_n(\tau)| \).

5. RESULTS

First, we provide the summary statistics of the model variables (Table 1). The results of the Jarque-Bera test suggest that it is adequate to use a quantile-based approach because it is robust to asymmetrically distributed data. Additionally, we check the suitability of using the quantile cointegration test of Xiao (2009) by checking for the presence of nonlinearity in the relationship between \( \text{ID}_t \) and \( Z_t \) through the BDS test by (Brock et al. 1996). Table 1 also reports the results of the BDS test, which suggest rejection of the null hypothesis of identical and independent residuals at the 1% significance. This provides evidence that the association between \( \text{ID}_t \) and \( Z_t \) is nonlinear. Hence, a linear model might not capture the true nature of the causal flows between \( \text{ID}_t \) and \( Z_t \). Therefore, we do not perform the Johansen (1991, 1995) cointegration analysis; instead, we implement a quantile cointegration test to capture the reactions of \( \text{ID}_t \) to the changes in \( Z_t \) corresponding to different quantiles.
Table 1. Summary Statistics and BDS test results

<table>
<thead>
<tr>
<th></th>
<th>ID&lt;sub&gt;t&lt;/sub&gt;</th>
<th>Z&lt;sub&gt;t&lt;/sub&gt;</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>6041,18</td>
<td>5578,30</td>
</tr>
</tbody>
</table>

BDS Test for the residuals of ID<sub>t</sub>

<table>
<thead>
<tr>
<th>Dimension</th>
<th>BDS Statistic</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>P-value.</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0,01**</td>
<td>0,01</td>
<td>2,55</td>
<td>0,01</td>
</tr>
<tr>
<td>3</td>
<td>0,03***</td>
<td>0,01</td>
<td>3,42</td>
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</tr>
<tr>
<td>4</td>
<td>0,04***</td>
<td>0,01</td>
<td>3,50</td>
<td>0,00</td>
</tr>
<tr>
<td>5</td>
<td>0,03***</td>
<td>0,01</td>
<td>3,15</td>
<td>0,00</td>
</tr>
<tr>
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<td>0,01</td>
<td>3,13</td>
<td>0,00</td>
</tr>
</tbody>
</table>

BDS Test for the residuals of Z<sub>t</sub>

<table>
<thead>
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<th>Dimension</th>
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<th>Std. Error</th>
<th>z-Statistic</th>
<th>P-value.</th>
</tr>
</thead>
<tbody>
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<td>0,01</td>
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<tr>
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<td>0,01</td>
<td>3,68</td>
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<td>6</td>
<td>0,04***</td>
<td>0,01</td>
<td>3,94</td>
<td>0,00</td>
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</tbody>
</table>

Note: This table presents the descriptive statistics of the variables ID<sub>t</sub> and Z<sub>t</sub>. Additionally, the table also presents the results of the BDS test on the VAR residuals. The null hypothesis holds that the residuals are i.i.d. The values in parentheses are the p-values of the test. The asterisks *** and ** denote rejection of the null hypothesis at the 1% and 5% significance level, respectively.

Table 2 reports the results of the quantile unit root test. The test considers $H_0: a(\tau) = 1$ within Equation (3) for the quantiles $T = [0.05, 0.01, 0.15, ..., 0.95]$. Table 2 shows the persistence estimates ($\bar{a}$), the t-Statistics of the null hypothesis $H_0: a(\tau) = 1$, and the critical values (CV) of the test. We include 10 lags of the difference of the dependent variable to avoid serial correlation of the residuals. We can see that ID<sub>t</sub> and Z<sub>t</sub> are non-stationary at the 5% significance level across all the quantiles of the conditional distribution. However, $\Delta ID_t$ and $\Delta Z_t$ are stationary at the 5% significance level across practically all the quantiles of the conditional distribution. Thus, we may conclude that ID<sub>t</sub> and Z<sub>t</sub> are I(1) processes.
Table 2. Quantile autoregression unit root analysis

<table>
<thead>
<tr>
<th>τ</th>
<th>$\hat{\alpha}$</th>
<th>$t$-statistic</th>
<th>$\hat{\alpha}$</th>
<th>$t$-statistic</th>
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<td>-3.32</td>
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<td>-3.41</td>
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<td>-2.70</td>
<td>0.16</td>
<td>-8.03</td>
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<tr>
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<td>0.98</td>
<td>-1.81</td>
<td>0.99</td>
<td>-1.17</td>
<td>-2.98</td>
<td>0.21</td>
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<tr>
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<td>0.05</td>
<td>1.00</td>
<td>-0.12</td>
<td>-2.51</td>
<td>0.06</td>
<td>-7.22</td>
<td>-2.45</td>
<td>0.25</td>
<td>-4.75</td>
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</table>

Note: Bold values indicate that the variable is stationary at the 5% significance level.

Since $ID_t$ and $Z_t$ are I(1) processes, we can implement the quantile cointegration test of Xiao (2009) to study whether the variables are cointegrated and whether the cointegrating relationship changes over the distribution. We include two lags and two leads of $(\Delta Z_t, \Delta Z_t^2)$ in the quantile cointegrating model (Equation 7). Table 3 shows the results of the quantile cointegration test, which suggests evidence of a (nonlinear) cointegration relationship between the quantiles of $ID_t$ and $Z_t$ at the 5% significance level. Thus, we find a long-run equilibrium relationship between $ID_t$ and $Z_t$, as postulated by the Supermultiplier approach to growth (Equation 2).
Table 3. Quantile cointegration test

<table>
<thead>
<tr>
<th>Model</th>
<th>Coefficient</th>
<th>Sup(\tau)(V_n(\tau))</th>
<th>CV1</th>
<th>CV5</th>
<th>CV10</th>
</tr>
</thead>
<tbody>
<tr>
<td>ID(_t) vs Z(_t)</td>
<td>(\beta)</td>
<td>136,611***</td>
<td>35,952</td>
<td>26,881</td>
<td>23,281</td>
</tr>
<tr>
<td></td>
<td>(\gamma)</td>
<td>0.014***</td>
<td>0.003</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Z(_t) vs ID(_t)</td>
<td>(\beta)</td>
<td>25,476***</td>
<td>10,871</td>
<td>8,249</td>
<td>7,082</td>
</tr>
<tr>
<td></td>
<td>(\gamma)</td>
<td>0.021***</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: This table presents the results of the quantile cointegration test of Xiao (2009) between ID\(_t\) and Z\(_t\). We test the stability of the coefficients \(\beta\) and \(\gamma\) in the quantile cointegration model (Equation 16). CV1, CV5 and CV10 denote the critical values of statistical significance at 1%, 5% and 10%, respectively. We used 50,000 Monte Carlo simulations to obtain the critical values. We employ an equally spaced grid of 19 quantiles to calculate the test statistic of the quantile cointegration models ID\(_t\) vs Z\(_t\) and Z\(_t\) vs ID\(_t\). The asterisks *** and ** denote rejection of the null hypothesis at the 1% and 5% significance level, respectively.

Next, we implement the quantile cointegration model specified in Equation (7).

The nonlinear cointegrating relationship between ID\(_t\) and Z\(_t\) is represented by \(\beta(\tau)\) and \(\gamma(\tau)\).

Table 4. Quantile cointegration model: estimated coefficients

| \(\tau\) | ID\(_t\) vs Z\(_t\) | Z\(_t\) vs ID\(_t\) |
|---------|----------------|----------------|----------------|
|         | \(\beta(\tau)\) | \(\gamma(\tau)\) | \(SM(\tau)\) | \(\beta(\tau)\) | \(\gamma(\tau)\) |
| 0.05    | 1,972***        | -0,004***       | 2,662         | 0,644***      | -0,000         |
| 0.10    | 1,937***        | -0,003**        | 2,704         | 0,632***      | -0,000         |
| 0.15    | 2,046***        | -0,004***       | 2,658         | 0,594***      | 0,000          |
| 0.20    | 2,045***        | -0,004***       | 2,657         | 0,627***      | -0,000         |
| 0.25    | 1,990***        | -0,004***       | 2,680         | 0,627***      | -0,000         |
| 0.30    | 2,003***        | -0,004***       | 2,693         | 0,592***      | 0,000          |
| 0.35    | 1,999***        | -0,004***       | 2,689         | 0,576***      | 0,000          |
| 0.40    | 1,911***        | -0,003**        | 2,678         | 0,558***      | 0,000          |
| 0.45    | 1,817***        | -0,001          | 2,662         | 0,553***      | 0,000          |
| 0.50    | 1,809***        | -0,001          | 2,731         | 0,547***      | 0,000          |
| 0.55    | 1,786***        | -0,001          | 2,708         | 0,539***      | 0,001*         |
| 0.60    | 1,712***        | -0,000          | 2,634         | 0,536***      | 0,001*         |
| 0.65    | 1,636***        | 0,000           | 2,706         | 0,529***      | 0,001**        |
| 0.70    | 1,568***        | 0,000           | 2,646         | 0,521***      | 0,001***       |
| 0.75    | 1,488***        | 0,001           | 2,643         | 0,509***      | 0,001***       |
| 0.80    | 1,554***        | 0,001           | 2,632         | 0,494***      | 0,001***       |
| 0.85    | 1,554***        | 0,001           | 2,632         | 0,498***      | 0,001***       |
| 0.90    | 1,508***        | 0,001           | 2,586         | 0,478***      | 0,001***       |
| 0.95    | 1,216***        | 0,004***        | 2,526         | 0,443***      | 0,001***       |

Note: This table displays the estimated coefficients of the quantile cointegration model (Equation 16). The asterisks ***; ** and * refer to rejection of the null hypothesis at the 1%, 5% and 10% significance level, respectively.
Table 4 shows the estimated cointegrating coefficients $\hat{\beta}(\tau)$ and $\hat{\gamma}(\tau)$ of Equation (7). The estimated coefficients of $\gamma(\tau)$, despite statistically significant at some quantiles, are close to zero for both models ($ID_t$ vs $Z_t$ and $Z_t$ vs $ID_t$). On the other hand, the estimated coefficients of $\beta(\tau)$ for the model $ID_t$ vs $Z_t$ (which is our proposed cointegration model) are positive and statistically significant at the 1% level for all quantiles.

Finally, we highlight that, since the effect of $Z$ on $ID$ corresponds to $SM - 1$ (see Equation 2), we estimate the value of the SM according to Equation (7), i.e., $SM_t = (\hat{\beta}(\tau) + 2\hat{\gamma}(\tau)Z_t) + 1$. Our results suggest that the value of the supermultiplier is above two in all quantiles of the conditional distribution. This implies that the supermultiplier effect of autonomous demand on output is relatively independent of extreme and central quantiles and thus possible regime changes. The estimated coefficients of $\beta(\tau)$ for the model $Z_t$ vs $ID_t$ are also positive and statistically significant at the 1% level for all quantiles; however, as expected, their value is below 1.

Macroeconomic variables are generally affected by exogenous shocks such as political regime shifts, international conflicts, financial or trade liberalization and unexpected changes to business conditions (Chang et al., 2015). However, the stability of the cointegrating coefficients is an important assumption underlying traditional linear estimations. While many economic indicators exhibit non-linear as well as time-varying processes, the change in the relationship between autonomous and induced demand may also give rise to a time-varying long-run equilibrium. Through a cointegration model with quantile-varying coefficients, we demonstrate that the long-run equilibrium relationship between autonomous and induced demand is robust to exogenous shocks and changes in the parameters.

5. CONCLUSIONS

The extension beyond the short run of the principle of effective demand is at the heart of contemporary studies in Post-Keynesian macroeconomics. Within this broad research agenda, in recent years a class of models that postulate that long-run economic growth is driven by autonomous demand and whose main example is the so-called supermultiplier has gained increasing popularity. Most of the related empirical literature
on the supermultiplier has focused on whether there is a cointegrating relationship between non-capacity-creating autonomous demand and final aggregate demand. However, with insights from some empirical literature on demand-led growth, we argue that autonomous demand and final aggregate demand might be related by national accounting construction, because the former is a component of the latter (Michaely 1977). To deal with this issue, we have dynamically analyzed the relationship between autonomous demand and final demand net of autonomous demand (induced demand).

Additionally, we have considered that the long-run cointegrating relationship between autonomous demand and induced demand might be subject to changes over the conditional distribution; being both variables nonlinearly interrelated, i.e., might be regime-dependent. Thus, we have tested the long-run equilibrium relationship between $ID_t$ and $Z_t$ across various quantiles of the conditional distribution of the variables between 1960 and 2019.

We have found that autonomous demand and induced demand are cointegrated across all quantiles of the conditional distribution of the variables. Thus, there is evidence of a long-run equilibrium relationship between these two variables, so that our results empirically support a theoretical approach such as the Supermultiplier. This long-run equilibrium relationship suggests us to complement our study with historical causal determinants. This is our goal for the future: to add historical and institutional depth to our empirical studies within the supermultiplier approach. In this sense, Stock-flow consistent models (Lavoie and Godley 2001), along with nonlinear time series methodologies (see Passarella, 2019), appear as promising complementary tools for the historical analysis.

REFERENCES


