PROFITABILITY AS A DRIVER OF INVESTMENT: EVIDENCE FROM BRAZILIAN INDUSTRIAL SECTORS

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Abstract: We explore empirically the short- and long-run effects of the profit rate and its components (profit share, output-capital ratio, capacity-capital ratio, and capacity utilization) on investment behavior in the Brazilian industrial sector. We employ three-digit industrial data covering the period from 1996 to 2017, which we analyze using linear dynamic panel data models. At high levels of confidence, the statistically significant results from estimating different specifications of the investment function are the following. The profit rate has both short- and long-run positive effects on industrial investment as a ratio of the capital stock. As for the components of the profit rate, industrial investment as a ratio of the capital stock is positively affected by the output-capital ratio and the rate of capacity utilization (actual output as ratio of capacity output) in the short and long run, positively impacted by the ratio of capacity output to capital only in the long run, and not affected by the profit share in either the short or long run.

Keywords: Investment; industrial sector; profitability; capacity utilization; dynamic panel models.

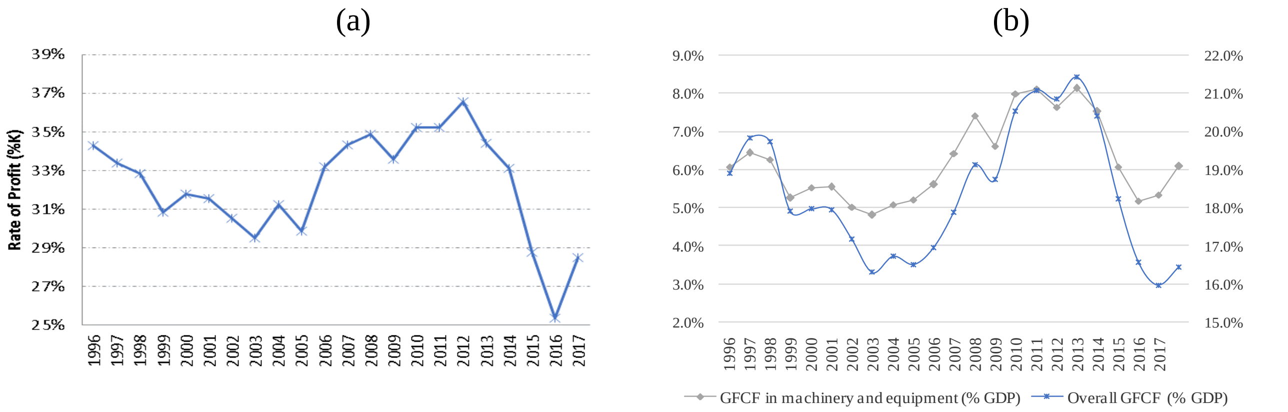
JEL Classification: C23; E22; E25; L60.

1. Introduction

The declining trajectory of investment has been a negative feature of the performance of the Brazilian economy in recent years. In fact, the gross fixed capital formation (GFCF) as a proportion of GDP fell from 21.8% in 2013 to 15.3% in 2016, reaching 16.1% in 2019. The GFCF in machinery and equipment followed the trajectory of the overall GFCF, having also experienced a significant drop in the same period. Consequently, it is timely and pressing to empirically explore the determinants of investment in the Brazilian industrial sector.

Figure 1 (a) shows the cycle of expansion and contraction experienced by the average profit rate in the Brazilian industrial sector starting in the mid-1990s. Especially noteworthy is the high positive correlation between the average industrial rate of profit and the overall GFCF and GFCF in machinery and equipment in Figure 1 (b). Thus, the possibility arises that the industrial profit rate exerts a causal impact on the investment behavior in the Brazilian industrial sector, and the purpose of this paper is to explore such a possibility. To that end, we use a large sample of three-digit industrial data totalling 111 industries for the period from 1996 to 2017, which we analyze using linear dynamic panel data models. The empirical strategy pursued in this paper is similar to that adopted in Basu and Das (2017), with the use of a dynamic approach allowing the estimation of the contemporary and long-run causal effects of the industrial profit rate and its components on industrial investment. This investigation fills a significant void in the empirical literature on the impact of the profit rate on economic activity in Brazil, as such existing studies typically deal with the overall economy (see, e.g., Marquetti et al., 2010, and Martins and Rugitsky, in press).

Figure 1: Investment and Profitability in Industrial Sectors in Brazil.



Source: (1) GDP - market prices, gross fixed capital formation and machine and equipment (2010 prices); (2) Profitability of the industrial sectors; Annual Industrial Survey - Company (PIA-Empresa).[1]

We find robust evidence that the industrial profit rate exerts short- and long-run positive effects on the flow of industrial investment as a proportion of the capital stock (or rate of capital accumulation). Regarding the components of the industrial profit rate, the flow of industrial investment as a ratio of the capital stock is positively impacted by the output-capital ratio and the rate of capacity utilization (actual output as a ratio of capacity output) in the short and long run, positively impacted by the ratio of capacity output to capital only in the long run, and not impacted by the profit share in either the short or long run.

The remainder of this paper progresses as follows. Section 2 outlines the four specifications of the investment function to be empirically tested, all of which are predicated upon the independence of the flow of investment from any prior flow of saving. Section 3 describes the elements of the empirical methodology to be followed in the estimations, while Section 4 presents and discusses the main results. Finally, Section 5 briefly concludes.

2. Determinants of investment

A key feature of the contributions of Keynes (1936) and Kalecki (1971) on the determinants of investment decisions is the refutation of the view that available savings are automatically transformed into investment. Given the independence of current investment from prior saving, the issue arise as to how investment decisions are determined. Motivated by the high positive correlation between the rate of profit and investment behavior in the Brazilian industrial sector pictured in Figure 1, let us outline the specifications of the investment function to be empirically tested down the road.

A natural specification of the investment function having profitability as the major determinant follows Kalecki (1935) and Robinson (1962) in assuming that current investment as a ratio of the existing capital stock depends positively on the expected profit rate, where the latter is the flow of expected real profits as a proportion of the existing capital stock. Adopting the further assumption often made by both Kalecki and Robinson themselves that the current profit rate is a reliable proxy of the expected profit rate, we arrive at the following specification of what we refer to as the Robinsonian

[1]Data for the profitability of the industrial sectors were computed according to (10) presented later, using data from the Annual Industry Survey – Company (Tables 101-106), which is conducted by the Brazilian Institute of Geography and Statistics (IBGE). The profit rate in Figure 1 was calculated as the average across the 111 three-digit industrial sectors, with values falling outside of the interval defined by the 1st and 99th percentiles being dropped from the sample.

investment function:

(1) $$\frac{I}{K} = \alpha + \beta_1 r ,$$

where I / K denotes the current investment as a ratio of the existing capital stock, or rate of capital accumulation, $r = \Pi / K$ is the rate of profit defined as the flow of real profits, Π, as a proportion of the existing capital stock, while α and β_1 are strictly positive parameters. As we intend to focus on the impact of profitability, other relevant factors that might affect investment are assumed to be captured by the autonomous component given by α. For instance, the latter captures the state of business confidence or animal spirits (Keynes, 1936). A rationale for the specification in (1) is that the current profit rate is an index of expected future earnings and also both provides internal funding for investment and makes it easier for firms to obtain external funding.

However, Bhaduri and Marglin (1990) argue for a formulation of investment decisions as a function of the profit share, rather than the profit rate, on the ground that this clearly separates the two different influences at work, whereas the rate of profit reflects the dual influences of profit share and capacity utilization. The underlying reason is that the rate of profit can be straightforwardly decomposed as $r = (\Pi / Y)(Y / Y^*)(Y^* / K) = hz\nu$, where $h = \Pi / Y$ is the profit share in income, with Y being aggregate income, $z = Y / Y^*$ is the rate of capacity utilization, with Y^* being the level of capacity (or potential) output, and $\nu = Y^* / K$ is the capacity-capital ratio. It is typically assumed in the related literature the constancy of the capacity-capital ratio, so that to save on dimensionality the output-capital ratio, $\gamma = Y / K$, can be used as a proxy of the rate of capacity utilization, given that the latter can be decomposed as $z = Y / Y^* = (Y / K)(K / Y^*)$. In this case, the rate of profit can be alternatively expressed as $r = (\Pi / Y)(Y / K) = h\gamma$. According to Bhaduri and Marglin (1990), to use the rate of profit in the specification of investment behavior is tantamount to assume that a given rate of profit will produce the same level of investment as results from a high capacity utilization and a low profit share or from low capacity utilization and a high profit share. In other words, a specification of the investment function featuring the rate of profit, as in (1) above, is insensitive to the influence of the existing capacity utilization, e.g., it neglects the possibility that, despite a high profit margin, firms may not be willing to invest in additional capacity if massive excess capacity already exists. On the basis of such discussion introduced by Bhaduri and Marglin (1990), the next specification of investment behavior to be tested later, to which we refer as the Bhaduri-Marglin investment function following Basu and Das (2017), is given by:

(2) $$\frac{I}{K} = \alpha + \beta_2 h + \beta_3 z ,$$

where β_2 and β_3 are strictly positive parameters. In the specification above, as in (1), the autonomous component given by α captures, for instance, the state of business confidence or animal spirits. Meanwhile, following Steindl (1952), the rate of capital accumulation is assumed to depend positively on the rate of capacity utilization due to several effects.[2] Although we follow Basu and Das (2017) in

[2] Steindl (1952) argues that firms plan excess capacity in order to be ready for a sudden expansion of sales. The existence of fluctuations in demand implies that the producer wants to be in a boom first, and not to leave the sales to new competitors who will press on her market when the boom is over. Besides, it is not possible for the producer to expand her capacity step

referring to the specification in (2) as the Bhaduri-Marglin investment function, this specification is different from that typically used in models of growth and distribution following the contribution in Bhaduri and Marglin (1990), where the rate of capacity utilization is proxied by the output-capital ratio instead of represented by $z = Y / Y^*$.

We follow Basu and Das (2017) in also testing a specification of the investment function which does not impose any *a priori* restriction on the effect of the three separate components of profitability on investment behavior.[3] Therefore, the next specification of investment behavior to be tested herein, to which we refer as the Foley-Michl investment function following the reference by Basu and Das (2017) to Foley and Michl (1999, p. 188), is given by:

(3) $$\frac{I}{K} = \alpha + \beta_4 h + \beta_5 z + \beta_6 \nu ,$$

where β_4, β_5 and β_6 are strictly positive parameters.

A troublesome feature of the more inclusive specification in (3), however, is that it requires the estimation of an unobservable macroeconomic variable such as capacity output, given the inclusion of the capacity-capital ratio, $\nu = Y^* / K$, as a possible determinant of investment. In order to circumvent this problem, recall from above that the rate of profit can be alternatively decomposed as $r = \Pi / K = (\Pi / Y)(Y / K) = h\gamma$. In the latter, the output to capital ratio is not seen as a proxy for the rate of capacity utilization by assuming the constancy of the capacity-capital ratio, as in Bhaduri and Marglin (1990) and most of the Kalecki-Steindl literature on demand-led growth initiated with the contributions in Rowthorn (1982) and Dutt (1984), but as a measure of capital productivity, a technological factor, as in Basu and Vasudevan (2013).[4] Thus, the final specification of investment behavior to be tested, which we dub Basu-Vasudevan investment function, is represented by:

(4) $$\frac{I}{K} = \alpha + \beta_7 h + \beta_8 \gamma ,$$

where β_7 and β_8 are strictly positive parameters.

3. Metodology

3.1 Database and methodology of construction of variables

This study uses data from the Annual Industrial Survey - Company (PIA-EMPRESA) of the

by step as her market grows due to indivisibility and durability of the plant and equipment. There is also the strategic issue of entry deterrence: if prices are sufficiently high, entry becomes feasible even where capital requirements are great; thus, the holding of excess capacity allows imperfectly-competitive firms to confront new entrants by suddenly raising supply and driving prices down.

[3] According to Basu and Das (2017), "ignoring the capacity-capital ratio as a determinant of investment is tantamount to imposing the restriction that the contemporaneous impact of technological change on investment is zero or that the capacity-capital ratio is the same across all firms (and is, hence, part of the intercept). This is both theoretically and empirically unwarranted." (p. 58)

[4] "The advantage of using this decomposition (rate of profit = profit share × capital productivity) is that we can avoid estimating an unobservable quantity such as 'capacity output', without which the capacity utilisation rate cannot be defined. In effect this decomposition allows fluctuations in aggregate demand to impact on both profit shares and capital productivity instead of concentrating on its effect on the capacity utilisation rate alone. This is more realistic because aggregate demand fluctuations can impact not only aggregate output (in comparison to 'capacity' output) but also income distribution and technological factors." (Basu and Vasudevan, 2013, p. 73)

Brazilian Institute of Geography and Statistics (IBGE). The presentation of information follows standards established by IBGE, providing different perspectives of consultation. A first consideration is related to the sampling process of the survey. The total sample consists of two parts, which are called panel and probabilistic sample. The panel includes companies with their respective local units, which, according to the selection register, had 30 or more employees. These companies are included in the sample, and this part is called the right stratum. Given the panel data methodology used in this study, companies with less than 30 employees were left out.

A second consideration concerns the unit of observation, that is, whether the source of information refers to the company as a whole or solely to the local unit. Information on the investment structure is made available by IBGE exclusively for the company observation unit. Under this perspective, information is presented for Brazil as a whole, without the discrimination by federation units (states).

The available information for the period from 1996 to 2007 is organized according to the National Classification of Economic Activities - CNAE 1.0, and, as of 2007, to the CNAE 2.0 version.[5] In CNAE 2.0, new support sectors for the main activity were created, with the result that the compatibility of the two methodologies requires a database adjustment work that is not directly provided by IBGE.[6] Thus, we based this study on the methodology developed by GIC-IE/UFRJ in order to perform the integration of the periods, obtaining a data panel for 111 sectors and a 22-year period. CNAE 2.0 is compatible with the International Standard Industrial (ISIC/CIIU 4).

Since the sectoral capital stocks are not directly available on the PIA database, we will make use of the well-known and widely used perpetual inventory methodology to estimate them. At the beginning of a given period (year) $t+1$ the net capital stock of sector *i*, denoted by $K_{i,t+1}$, depends on the net capital stock of this sector at the beginning of the previous period, given by $K_{i,t}$, the gross investment of the *i*-th sector made in the previous period, denoted by $I_{i,t}$, and the physical depreciation of the capital in this sector occurred over period *t*, given by $D_{i,t}$. More precisely, based on these determinants we can establish the following capital accumulation equation:

$$(5) \qquad K_{i,t+1} = K_{i,t} + I_{i,t} - D_{i,t} .$$

Let us assume geometric depreciation at a constant rate $\delta \in (0,1) \subset \mathbb{R}$ for any sector *i*, so that $D_{i,t} = \delta K_{i,t}$, which permits to re-write (5) as follows:

$$(5\text{-a}) \qquad K_{i,t+1} = (1-\delta)K_{i,t} + I_{i,t} .$$

Therefore, given the depreciation rate and the gross investment time series of the *i*-th sector, the capital stock time series for this sector is obtained through recursion using (5-a) from a given initial value K_{i,t_0}. In our case, as usual, we do not have this information, so that we need to obtain this boundary condition indirectly. To that end, we will use the steady growth approach (Blades, 2015).

Drawing on Blades (2015), we can approximate the sectoral capital stock at the beginning of a given

[5]Information about CNAE 1.0 and CNAE 2.0, with multiple decimal places, as well as the compatibility with international classifications such as CIIU (in its different versions), can be consulted on the website of the National Classification Commission (CONCLA) at https://concla.ibge.gov.br/.
[6]IBGE provides a conversion spreadsheet that can be obtained at:
https://cnae.ibge.gov.br/classificacoes/correspondencias/atividades-economicas.html.

period t_0 as a result of past net investments made in earlier years, that is:[7]

(6) $$K_{i,t_0} \cong \sum_{j=1}^{\infty}(1-\delta)^{j-1} I_{i,t_0-j} \, .$$

Assuming that the *i*-th sector grows at the constant rate $g > 0$ exogenously determined until the period t_0, we can establish that $I_{i,t_0-j} = I_{i,t_0-1} \big/ (1+g)^{j-1}$ for all $j = 1, 2, \ldots$, which allows to re-writing (6) as follows:

(6-a) $$K_{i,t_0} \cong \sum_{j=1}^{\infty}(1-\delta)^{j-1} \frac{I_{i,t_0-1}}{(1+g)^{j-1}} = I_{i,t_0-1} \sum_{j=1}^{\infty}\left(\frac{1-\delta}{1+g}\right)^{j-1} = \frac{I_{i,t_0-1}}{1-\dfrac{1-\delta}{1+g}} = \frac{(1+g)I_{i,t_0-1}}{g+\delta} = \frac{I_{i,t_0}}{g+\delta} \, .$$

Thus, given g and δ, it is only necessary to have I_{i,t_0} in order to estimate K_{i,t_0} for each sector *i*. As pointed out in Berlemann and Wesselhöft (2014, p. 4), although it demands few information, the estimate of K_{i,t_0} depends significantly on the initial level of the sectoral investment, given that small disturbances on this initial value would lead to a strongly biased estimate of the sectoral capital stock at the initial period.

Considering the high sensitivity of the sectoral trajectory of the capital stock with respect to the initial value of the sectoral investments, we use a simple and usual method to smooth out the impact of the initial value of the sectoral investment, namely we estimate the initial investment of sector *i* as the average annual investment of our sample, which begins at 1996 ($t_0 + 1$) and ends at 2017 ($t_0 + 22$). In sum, the initial investment of each sector *i* in the initial period t_0 can be estimated as follows:

(7) $$I_{i,t_0} = \frac{\sum_{t=t_0+1}^{t_0+22} I_{i,t}}{22} \, .$$

Sectoral investment data are also not made available by PIA in a specific series. Based on Souza and Pinto (2015), the series of sectoral investment is obtained from three other series that are collected in the survey (in the fixed assets table) as an estimation of the investment, namely: i) third-party acquisitions and their own production; ii) improvements); and iii) downfalls. Also, since not all PIA participating companies declare acquisitions, improvements and downfalls, in order to obtain investment series by sector, we attributed weight to the values depending on the number of reporting companies and then multiplied the result by the total number of survey respondents, so that we compute the investment in nominal terms (i.e. at current prices) of sector *i* in the year *t*, denoted by $NI_{i,t}$, based on the following aggregation rule:

(8) $$NI_{i,t} = \left(\frac{VA_{i,t}}{\# RA_{i,t}} + \frac{VI_{i,t}}{\# RI_{i,t}} + \frac{VD_{i,t}}{\# RD_{i,t}} \right) \# SR_{i,t} \, ,$$

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[7] As explained in Blades (2015, p. 376, footnote 10), in (6) we have an approximation because, by analytical simplicity, the depreciation in the period $t_0 - 1$ is disregarded.

where VA_t is the nominal value of industry asset acquisitions (third-party acquisitions and their own production) in the sector *i* the year *t*; $VI_{i,t}$ is the nominal value of improvements, that is, enhancements and improvements to stationary assets (including expenditures required to put certain items in place and conditions for use in the company's operating process); in turn, $VD_{i,t}$ is the sector i asset downfalls in year t, which is the residual value of the assets, that is, acquisition costs monetarily corrected and deducted from the depreciation account balances at the date of downfalls. Finally, $\#RA_{i,t}$, $\#RI_{i,t}$, and $\#RD_{i,t}$ represent the number of reporting companies with respect to acquisitions, improvements and downfalls, respectively, and $\#SR_{i,t}$ is the total number of survey PIA respondent companies. It is also the same number of companies that display data such as output data, revenues, and costs, among others.

An implicit limitation of this methodology is the assumption that, on average, non-declarant companies made the same investment as declarant companies. Alves and Silva (2008) consider this data imputation to be valid when comparing PIA companies regarding their patterns of growth in net revenue and the number of employees: as there are no significant investment differences between declarants and non-declarants, the authors conclude that there is no reporting bias in the survey. If there were any, it would be expected that non-declarant companies would have made smaller investments, which would be evident by the lower net revenues or number of employees.[8]

Having constructed the nominal investment series $\left\{NI_{i,t}\right\}_{t=1}^{22}$ for each sector *i* as defined in (8), we obtain the sectoral investment series $\left\{I_{i,t}\right\}_{t=1}^{22}$ in real terms at constant prices of 2017 using the Wholesale Price Index (IPA), an index that is also used in Souza and Pinto (2015). Based on this sectoral investment series expressed in real terms, we make use of (7) to calculate the initial sectoral investment I_{i,t_0} for each sector *i*. Given that, and, following Souza and Pinto (2015), setting $\delta = 0.07$ and $g = 0.02$ for each sector *i*, we estimate by (6) the initial sectoral capital stock K_{i,t_0} for each sector *i*. Finally, using this initial condition and the capital accumulation equation in (5-a) we obtain by recursion the sectoral capital stock time series $\left\{K_{i,t}\right\}_{t=1}^{22}$ for each sector *i*.

Basu and Das (2017) calculate income from value-added, excluding amounts spent with wages in productive work, $w_{i,t}$, rent expenses, $\rho_{i,t}$, and interest expenses, $\iota_{i,t}$. It turns out that the series of value-added began to be released as part of the PIA survey only in 2007, with the change to CNAE 2.0. Moreover, in the PIA, value-added is an adjustment calculation, starting from the gross value of industrial production (GVIP) and intermediate consumption (IC). A proxy of value-added use is usually the value of industrial transformation (VIT), a variable obtained by the difference between the GVIP and the cost of industrial operations.[9] Thus, we maintain the form defined in Basu and Das (2017), with the replacement of value-added by VIT, which seems more appropriate to our data. Therefore, the flow

[8]Alves e Silva (2008) had access to detailed data of the PIA survey and used propensity score-matching in order to make data input, which aggregated companies with similar characteristics.

[9] The cost of industrial operations (COI) corresponds to the sum of the costs directly involved in production at the local industrial productive unit, over the course of one year, except for salaries and taxes. It represents the sum of the following variables: consumption of raw materials, auxiliary material and components, electricity costs, fuel consumption, parts and accessories for maintenance and machinery repair, industrial and maintenance services and repair of machinery and equipment for production provided by third parties.

of real profits of sector *I* in period *t* can be obtained as follows:

(9) $$\Pi_{i,t} = VIT_{i,t} - (w_{i,t} + \rho_{i,t} + \iota_{i,t}),$$

while the profit rate of *i*-th sector in period *t* can be calculated as:

(10) $$r_{i,t} = \frac{\Pi_{i,t}}{K_{i,t}} = \frac{VIT_{i,t} - (w_{i,t} + \rho_{i,t} + \iota_{i,t})}{K_{i,t}}.$$

In turn, the profit share of *i*-th sector in period *t*, $h_{i,t}$, is obtained using the flow of real profits and the value of industrial transformation of this sector in the period *t*, which is taken as a proxy for the value of production ($Y_{i,t}$) of this sector in the period *t*, that is:

(11) $$h_{i,t} = \frac{\Pi_{i,t}}{Y_{i,t}} = \frac{VIT_{i,t} - (w_{i,t} + \rho_{i,t} + \iota_{i,t})}{VIT_{i,t}},$$

while the respective sectoral capital-output ratio is computed as:

(12) $$\gamma_{i,t} = \frac{Y_{i,t}}{K_{i,t}} = \frac{VIT_{i,t}}{K_{i,t}}.$$

Finally, the rate of capacity utilization, $z_{i,t}$, and the capacity-capital ratio, $v_{i,t}$, of sector *i* are computed, respectively, as follows:

(13) $$z_{i,t} = \frac{Y_{i,t}}{Y^*_{i,t}} = \frac{VIT_{i,t}}{VIT^*_{i,t}},$$

and

(14) $$v_{i,t} = \frac{Y^*_{i,t}}{K_{i,t}} = \frac{VIT^*_{i,t}}{K_{i,t}},$$

where $VIT^*_{i,t}$ is the estimate for $Y^*_{i,t}$ obtained by fitting a Hodrick-Prescott (HP) filter to the *i*-th sector's VIT series, as in Basu and Das (2017).

3.2 Descriptive statistics

Based on the methodology described in the previous sub-section, we constructed time series of annual frequency of the capital stock, investment, profit rate, profit share, capacity utilization, capacity-capital ratio, and output-capital ratio. A variable representing the sectoral growth rate was constructed as a control variable, using the gross value of the industrial production ($GVIP$).

Table 1 presents descriptive statistics of our variables of interest. Given the different time trends observed for the profit rate in Figure 1, descriptive statistics are also presented for the following subperiods: (i) 1996-2003; (ii) 2004-2012; and (iii) 2013-2017. The average flow of investment as a percentage of the capital stock over the entire period was 7.4%, reaching 10.2% in the period 2004-2012, but falling considerably in the subsequent period 2013-2017 to reach 1.4%. The profit share remained relatively stable, with an average value of 65.2% over the whole period and the lowest value of 62.3% in the period 2013-2017. The capacity utilization measure, based on the potential (capacity) output obtained with the HP filter, reached an average value of 98.2% over the whole period. The capacity-capital ratio, also using the potential output measure provided by the HP filter, averaged 51.6%, while the ratio of output to capital showed an average value of 52.3%, both over the whole period. Finally, the average annual growth rate of all the sectors combined was 4.5% over the entire period, reached 8.1% in the period 2004-2012 period and dropped considerably to -0.6% in the period 2013-2017.

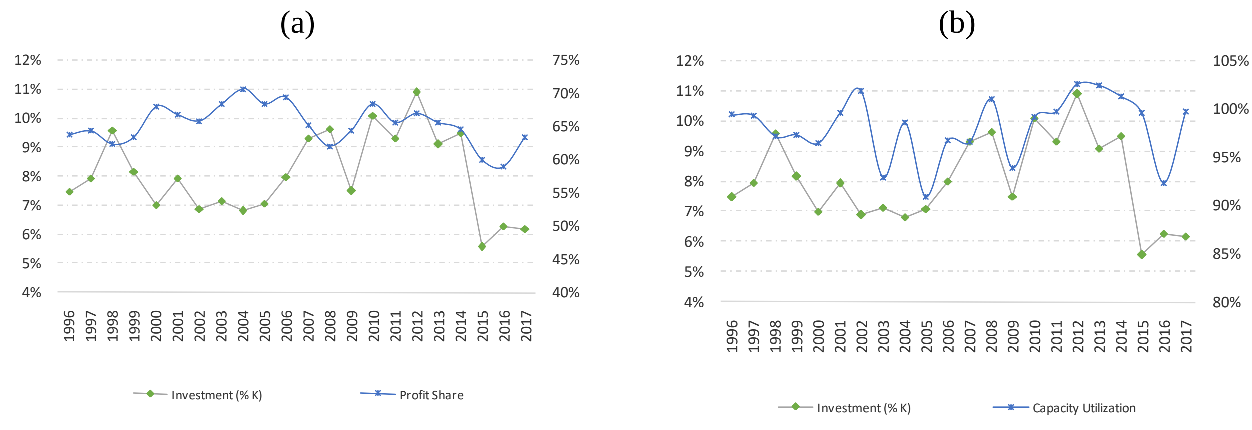
Table 1: Descriptive Statistics

Variable	1996-2017			1996-2003			2004-2012			2013-2017		
	N	Mean (%)	SD (%)	N	Mean (%)	SD (%)	N	Mean (%)	SD (%)	N	Mean (%)	SD (%)
Investment (% K)	2,376	7.4	62.2	864	8.0	17.2	972	10.2	84.3	540	1.4	111.7
Profit rate (r) (% K)	2,376	35.0	142.9	864	31.8	92.3	972	39.4	126.4	540	32.4	168.1
Profit share (h) (% VIT)	2,364	65.2	16.1	848	65.3	11.5	971	66.8	12.6	545	62.3	13.1
Capacity utilization (z) (% VTI)	2,392	98.2	20.5	864	98.2	19.7	978	97.7	15.1	550	99.1	14.4
Capacity-capital ratio (v)	2,376	51.6	232.6	864	45.2	147.8	972	57.6	242.4	540	51.0	323.6
Output-capital ratio (γ)	2,376	52.3	255.8	864	44.9	168.6	972	58.1	279.9	540	53.9	374.1
Sectoral growth (g) ($\Delta GVIP$)	2.255	4.5	50.9	742	3.5	21.4	967	8.1	73.4	546	-0.6	19.8

Source: Annual Industrial Survey - Company (PIA-EMPRESA), tables 101-106. In the last row, the growth rate of sectoral $GVIP$, as described in the next section, refers to a control variable intended to capture sector-specific factors, such as public policies, which possibly impact on the growth of a given sector.

Figure 2 displays the behavior of the rate of capital accumulation (flow of investment as a ratio of the capital stock) and the components of the profit rate over the considered period, with respective values shown in the left and right vertical axes, respectively. Visual inspection suggests that the behavior of the rate of capital accumulation is more closely correlated with the behavior of the capacity-capital ratio (panel (c)) and the output-capital ratio (panel (d)) than with the behavior of the profit share (panel (a)) and capacity utilization (panel (b)).

Figure 2: Investment and components of the profit rate (average across all sectors)



(c) (d)

Source: Annual Industrial Survey - Company (PIA-EMPRESA), tables 101-106. In order to avoid distortions in the representation of the trend of the profit rate, values below 1% and above 99% of the distribution were disconsidered.

3.3 Empirical strategy

Recall from Section 2 that a natural specification of investment behavior having profitability as the major determinant follows Kalecki (1935) and Robinson (1962) in assuming that investment as a ratio of the capital stock (or rate of capital accumulation) depends positively on the expected rate of profit. In the specification of the investment function in (1), the underlying assumption (often made by both Kalecki and Robinson themselves and the following literature) is that the current profit rate is a proxy for the expected profit rate.

However, as observed in Basu and Das (2017), a more reasonable specification features past and current profit rates determining expected profitability and, ultimately, investment behavior. In light of such an observation, our empirical strategy involves the use of a dynamic panel data approach to estimate the investment functions specified in Section 2. Drawing upon Basu and Vasudevan (2013) and Basu and Das (2017), the specifications to be estimated are the following:

$$(15)\quad \left(\frac{I}{K}\right)_{i,t} = \alpha\left(\frac{I}{K}\right)_{i,t-1} + \beta_1 r_{i,t} + \beta_2 r_{i,t-1} + \beta_3 r_{i,t-2} + \varphi g_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t},$$

$$(16)\quad \left(\frac{I}{K}\right)_{i,t} = \alpha\left(\frac{I}{K}\right)_{i,t-1} + \beta_4 h_{i,t} + \beta_5 h_{i,t-1} + \beta_6 h_{i,t-2} + \beta_7 \gamma_{i,t} + \beta_8 \gamma_{i,t-1} + \beta_9 \gamma_{i,t-2} + \varphi g_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t},$$

$$(17)\quad \left(\frac{I}{K}\right)_{i,t} = \alpha\left(\frac{I}{K}\right)_{i,t-1} + \beta_{10} h_{i,t} + \beta_{11} h_{i,t-1} + \beta_{12} h_{i,t-2} + \beta_{13} z_{i,t} + \beta_{14} z_{i,t-1} + \beta_{15} z_{i,t-2} + \varphi g_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t},$$

$$(18)\quad \left(\frac{I}{K}\right)_{i,t} = \alpha\left(\frac{I}{K}\right)_{i,t-1} + \beta_{16} h_{i,t} + \beta_{17} h_{i,t-1} + \beta_{18} h_{i,t-2} + \beta_{19} z_{i,t} + \beta_{20} z_{i,t-1} + \beta_{21} z_{i,t-2} + \beta_{22} v_{i,t} + \beta_{23} v_{i,t-1} + \beta_{24} v_{i,t-2} + \varphi g_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t},$$

where i and t indicate, respectively, the industrial sector and year, I/K is the flow of investment as a proportion of the capital stock, and the independent variables r, h, γ, z and v denote, respectively, the profit rate and its components, namely, the profit share, output-capital ratio, capacity utilization and capacity-capital ratio. Meanwhile, g denotes the growth rate of the gross value of industrial production ($GVIP$), μ_i are industrial sector fixed effects, δ_t are year fixed effects, and $\beta_1 ... \beta_{24}$ are the parameters yielding estimates of the contemporary and long-run impacts of profitability and their components on investment. An estimate of the contemporaneous effect of the rate of profit (or its components) on investment behavior is provided by the impact (or short-run) multiplier, while the respective long-run effect is captured by the long-run multiplier. The four specifications above are based, respectively, on the investment functions in Section 2 referred to as Robinsonian (in (1)), Basu-Vasudevan (in (4)), Bhaduri-Marglin (in (2)) and Foley-Michl (in (3)).

Thus, our estimated investment functions featuring in (15)-(18) are dynamic in nature, which conveniently allows for a lagged dependent variable and lags of the rate of profit or its components) to pick up dynamic effects. This way we can fruitfully estimate both impact (contemporaneous) and long-run multipliers of the rate of profit (or its components) with respect to investment behavior. Our unit of observation is each one of 111 industrial sectors of the Brazilian economy (at the three-digit level of analysis) in a given year, and we include the first lag of the dependent variable to capture a potential persistence in investment decisions, and we expect $\alpha < 1$, and two lags for the regressors involving the rate of profit or its components, given the potentially lagged nature of their influence (Basu and Das, 2017). We also include the sectoral growth rate g in order to isolate sector-specific effects (such as aggregate demand shocks, credit restrictions, and infrastructure) and dummies for each year so as to aggregate specific variations from year to year. The long-run multipliers for the dependent variable are obtained by adding up the contemporary and lagged coefficients and dividing through by $(1-\alpha)$, with confidence intervals being obtained by the delta method. Therefore, the impact multiplier of the rate of profit or any of its components is represented by $(\beta_{j_{i,t}} + \beta_{j_{i,t-1}} + \beta_{j_{i,t-2}})/(1-\alpha)$, with $j = 1, 2, ...24$.

The choice of estimation procedure should take into account the dynamic nature of the regressions to be run and the possibility that the explanatory variables are endogenous to investment behavior and, therefore, simultaneity or reverse causality have to be adequately controlled for (Pesaran, 2015). In order to deal with these problems, we follow Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) and use the Generalized Moments Method (GMM) to estimate the several parameters of the model. These estimators are based on differential regressions and instruments to control for unobserved periods and industry-specific effects. In addition, the method also uses previous observations of dependent variables as valid instruments. There are two approaches within the GMM approach, the first difference GMM and the System GMM. According to Ribeiro, McCombie and Lima (2020), the GMM difference method represents an advance over the fixed-effects estimators, given that the Arellano and Bond's (1991) first difference GMM estimator seeks to eliminate specific effects from each observation unit and also uses delayed observations of explanatory variables as instruments. Nonetheless, the first difference GMM method has a disadvantage in dealing with variables that tend to have a degree of persistence over time such as lagged effects of profitability (or its components) within a specific sector. This implies that we eliminate most of the variation in variables when using the first difference. In this context, delayed observations of explanatory variables tend to be weak instruments for differential variables, thus generating weak estimators.

In order to solve such a problem, Arellano and Bover (1995) and Blundell and Bond (1998) propose a new approach by creating a regression system on difference and level. The regression instruments used in the first difference remain the same in the GMM difference method. The instruments used in level regressions are the lagged differences of the explanatory variables. With this estimation technique, the explanatory variables can still be correlated with the specific effects of each sector, but the difference of these variables does not correlate with these sector-specific effects.

The validity of GMM estimators greatly depends on the exogeneity of the instruments used in the baseline model. Therefore, a first type of test refers to the test of exogeneity of the instruments that can be tested by employing the J statistics of the Hansen test. A rejection of the null hypothesis indicates that the set of instruments adopted and the treatment given to endogenous and exogenous instruments (control variables) are not valid, thus making the GMM estimator not consistent. Still regarding the validity of model specification, another commonly used test in this context is the difference-in-Hansen test, which is carried out by taking the difference in Hansen's J statistics between restricted regression (when regressors are treated as predetermined[10]) and unrestricted regression (when regressors are treated as endogenous). The difference in Hansen's J statistics is distributed as a chi-square random variable with the number of extra instruments in the restricted regression as their degree of freedom. The null hypothesis of the considered test is that the full set of instruments that come from treating regressors as predetermined is valid. Thus, failure to reject the null hypothesis suggests that constrained regression is preferred by data over unrestricted regression. Roodman (2009) advises researchers not to comfort themselves with a p value of Hansen's test below 0.10.[11]

The second type of test, which is also crucial, is the test to check for the presence of autocorrelation in regression errors, which is known as the Arellano-Bond test for AR (2) in the first difference. The null hypothesis of this test examines whether the difference regression residue is serially correlated in the second order. The first order serial correlation of the differential error term is usually observed even when the error term at the level is uncorrelated. The second order serial correlation of the residual difference implies that the error term is serially correlated. Therefore, the rejection of the null hypothesis indicates that the residual term is serially correlated and follows a moving average process of at least one order, as pointed out in Ribeiro, McCombie and Lima (2020). Consequently, a rejection of the null hypothesis suggests that the instruments used are inadequate and, therefore, higher lags may be required.

Our empirical strategy also included the estimation of the investment functions in (15)-(18) using the pooled OLS estimator and the fixed effects OLS estimator (*within*). According to Roodman (2009), although we are conscious that these are skewed estimators, they are useful in providing limits on "true" parameter values: the pooled OLS estimator is skewed up and the fixed effect estimator is skewed down (Roodman, 2009). Thus, reasonable estimates of System GMM parameters should be limited by these two estimates.

Finally, given the characteristics of our database and the specification of the models to be estimated, we followed Roodman's (2009) recommendations regarding the applicability of the System GMM estimators: i) "Small T and large N" panels, meaning few periods of time and many individuals; ii) a linear functional relationship; iii) a left-hand variable that is dynamic, dependent on its own past realizations; iv) independent variables that are not strictly exogenous, meaning that they are correlated

[10]According to Basu and Das (2017), in a context of panel data with dynamic effects, strictly exogenous regressors are not realistic because they discard the feedback of regression errors in period t for regressors in all future periods. While predetermined regressors allow this feedback, endogenous regressors also allow correlation between the regression error and the regressors at the same time. In this way, we discard the estimation with purely exogenous regressors and the choice between predetermined (or weakly exogenous) and endogenous regressors and done with the difference-in-Hansen test.

[11]As for the instruments, it is likely that a large number of instruments over-adjust the endogenous variables. The literature is not extremely specific in determining the maximum number of instruments to be used in each case. Roodman (2009) suggests, as a relatively arbitrary rule of thumb, that instruments should not exceed individual units on the panel (in our case, industrial sectors). As also used in Ribeiro, McCombie and Lima (2020), we try to keep the number of instrumental variables to a minimum and use the collapse function, available in the Xtabond2 package, to limit the proliferation of instruments.

with past and possibly actual error realizations; v) fixed individual effects; and vi) heteroscedasticity and autocorrelation within sectors, but not between them.

4. Results of econometric estimates

Before proceeding with regression analysis, we carried out panel unit root tests on all variables involved. In Table A.3 in the Appendix, we present results of a Fisher test for each such variable. In each test the null hypothesis is that all panels feature unit roots and the alternative hypothesis is that at least one panel is stationary. Our results suggest that we can safely reject the null hypothesis for all variables involved, so that our regression analysis does not face unit root and spuriousness problems.

The following tables report results for three specifications of the investment behavior in (15)-(18): (1) a pooled OLS estimator with year dummies; (2) a fixed effect (within) estimator, also featuring year dummies; and (3) a system GMM estimator with all regressors treated as either strictly exogenous or predetermined or endogenous, the choice between them being made employing a difference-in-Hansen.

4.1 Robinsonian investment function

Recall that the Robinsonian investment function in (1), the specification of which is estimated using (15), features investment as a ratio of the capital stock being positively related to the profit rate.

Table 2: Robinsonian investment function

	(1) Pooled OLS	**(2) Fixed Effect**	**(3) System GMM**$^{(2)}$
1 Lag of dep. var.$^{(1)}$	**0.415*****	**0.289*****	0.298***
	(0.028)	(0.032)	(0.032)
Profit rate	0.084	0.161*	**0.205****
	(0.058)	(0,085)	(0.095)
Sectoral growth	0.768***	0.799***	0.681***
	(0.101)	(0.117)	(0.123)
2 Lags of profit rate	Y	Y	Y
Groups	-	107	107
Observations	1,903	1,903	1,903
Hansen test of joint validity (*p*-value)$^{(3)}$	-	-	0.839
Difference-in-Hansen (*p*-value)$^{(4)}$	-	-	0.577
AR2 (*p*-value)$^{(5)}$	-	-	0.330
Year fixed effects	Y	Y	Y
Industrial sector fixed effects	N	Y	Y
Regressors treated as $^{(6)}$	-	-	PD
		Long-run Multiplier$^{(7)}$	
Profit rate$^{(7)}$	0.378***	0.923***	**0.808*****
	(0.051)	(0.094)	(0.183)

Notes: (1) In all three specifications, the dependent variable is the ratio of investment to capital stock (in logarithm and time lagged); (2) Two-step GMM estimation and standard errors have been corrected for finite sample bias following Windmeijer (2005); (3) The Hansen test regards over-identifying restrictions (the null hypothesis is that the instruments are valid); (4) The difference-in-Hansen test concerns instrument exogeneity (the null hypothesis is that the set of instruments is valid vis-à-vis the model with exogenous regressors); (5) AR2 refers to the autocorrelation test in the first different error in order 2 (the null hypothesis is that there is no autocorrelation); (6) SE: strictly exogenous; PD: predetermined but not strictly exogenous; and ED: endogenous; (7) Standard errors for long-run multipliers were computed using the delta method (which is based on expanding the Taylor series function to approximate variance calculations; see Hoeff, 2012); and (8) Levels of significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

For all considered specifications, we find that the profit rate exerts a positive and statistically significant contemporary and long-run impact on investment. For estimates with the system GMM, the contemporary profit rate multiplier is 0.205 and the long-run multiplier is 0.808. Consequently, a 1.0% increase in the profit rate would bring about a 0.21% and 0.81% increase in investment as a proportion of the capital stock in the short and long run, respectively. As for the robustness of these results, the *p*-value equal to 0.839 in the Hansen test confirms the joint validity of the instruments. Meanwhile, the Difference-in-Hansen test on the exogeneity of instruments corroborates the soundness of treating the regressors as predetermined. Also, the *p*-value for the error autocorrelation test is 0.33, which does not reject the null hypothesis of non-autocorrelation in the residuals. It then follows that these results on the positive effect of the profit rate on capital accumulation are robust, as their estimation through the system GMM is well specified.

4.2 Basu-Vasudevan investment function

Recall that the Basu-Vasudevan capital accumulation function in (4), the specification of which is estimated employing (16), features investment as a ratio of the capital stock varying positively with the profit share as a measure of profitability and the ratio of output to capital as a measure of capital productivity, a technological factor.

Table 3: Basu-Vasudevan investment function

	(1) Pooled OLS	**(2) Fixed Effect**	**(3) System GMM**$^{(2)}$
1 Lag of dep. var.$^{(1)}$	**0.434*****	**0.267*****	0.272***
	(0.031)	(0.035)	(0.036)
Profit share	-0.123	-0.202*	**-0.141**
	(0.098)	(0.108)	(0.188)
Output-capital ratio	0.458***	0.626***	**0.544*****
	(0.171)	(0.183)	(0.180)
Sectoral growth	0.473***	0.509***	0.606***
	(0.158)	(0.170)	(0.161)
2 Lags of profit share and output-capital ratio	Y	Y	Y
Groups	-	107	107
Observations	1,903	1,903	1,903
Hansen test of joint validity (*p*-value)$^{(3)}$	-	-	0.849
Difference-in-Hansen (*p*-value)$^{(4)}$	-	-	0.176
AR2 (*p*-value)$^{(5)}$	-	-	0.366
Year fixed effects	S	S	S
Industry fixed effects	N	S	S
Regressors treated as $^{(6)}$	-	-	PD
		Long-run Multiplier$^{(7)}$	
Profit share	0.183	-0.285	**-0.283**
	(0.166)	(0.184)	(0.325)
Output-capital ratio	0.432***	1.283***	**1.112*****
	(0.057)	(0.084)	(0.167)

Notes: Same as in Table 2.

For all specifications, surprisingly, we find that capital accumulation is negatively impacted by the profit share. However, this result is statistically significant only for specification (2), which is, as we are aware, a biased estimator for the considered model. For the system GMM estimator, although the profit share coefficient is also negative, we cannot accept that it is significantly different from zero, both in the contemporary and in the long-run multiplier. In fact, this result is already suggested by the behavior of the considered variables described in Figure 2(a). Meanwhile, we find that the ratio of output to capital has a positive and statistically significant contemporary and long-run impact on investment in all specifications, as suggested in Figure 2(d). For the system GMM estimator, the contemporary output-capital multiplier is 0.544 and the long-run multiplier is 1.112. Therefore, a 1.0% increase in the output-capital ratio as a measure of capital productivity would bring about a 0.54% and 1.11% increase in capital accumulation in the short and long run, respectively. Concerning the robustness of these results, the Hansen test and the Difference-in-Hansen test confirm the joint validity of the instruments, the Difference-in-Hansen test on the exogeneity of instruments corroborates the soundness of treating the regressors as predetermined, and the autocorrelation test allows us to accept the hypothesis of non-autocorrelation in the residuals.

4.3 Bhaduri-Marglin investment function

Recall that the Bhaduri-Marglin capital accumulation function in (2), the specification of which is estimated using (17), features investment as a ratio of the capital stock varying positively with the profit share as a measure of profitability and the rate of capacity utilization as an accelerator effect.

Table 4: Bhaduri-Marglin investment function

	(1) Pooled OLS	**(2) Fixed Effect**	**(3) System GMM**[(2)]
1 Lag of dep. var.[(1)]	**0.441***** (0.028)	**0.386***** (0.034)	0.388*** (0.041)
Profit share	-0.083 (0.071)	-0.081 (0.075)	**-0.099** (0.103)
Capacity utilization	0.528*** (0.183)	0.585*** (0.192)	**0.546***** (0.152)
Sectoral growth	0.587*** (0.149)	0.482*** (0.198)	0.655*** (0.165)
2 Lags of profit share and capacity utilization	Y	Y	Y
Groups	-	107	107
Observations	1,902	1,902	1,902
Hansen test of joint validity (p-value)[(3)]	-	-	0.751
Difference-in-Hansen (p-value)[(4)]	-	-	0.968
AR2 (p-value)[(5)]	-	-	0.744
Year fixed effects	S	S	S
Industry fixed effects	N	S	S
Regressors treated as [(6)]	-	-	PD
		Long-run Multiplier[((7)]	
Profit share	0.367** (0.172)	0.525** (0.231)	**0.067** (0.356)
Capacity utilization	0.903 (0.581)	0.660** (0.335)	**0.874**** (0.364)

Notes: Same as in Tables 2 and 3.

As obtained for the Basu-Vasudevan investment function, capital accumulation is found to vary negatively with the profit share. Yet this result is not statistically significant for any of the specifications, so we cannot accept that the respective contemporary and long-run multipliers are statistically different from zero. As for the rate of capacity utilization, we find that it has a positive and statistically significant contemporary impact on investment behavior in all specifications. For the system GMM estimator, the respective multiplier is 0.546, so that a 1.0% increase in capacity utilization would bring about a 0.55%

increase in capital accumulation in the short run. In fact, also for the system GMM estimator, capacity utilization has a statistically significant effect on investment behavior in the long run, and the respective multiplier is 0.874. As for the robustness of these findings, the Hansen test and the Difference-in-Hansen test confirm the joint validity of the instruments, the Difference-in-Hansen test on the exogeneity of instruments confirms the soundness of treating the regressors as predetermined, and the autocorrelation test allows accepting the hypothesis of non-autocorrelation in the residuals.

4.4 Foley-Michl investment function

Recall that the Foley-Michl capital accumulation function in (3), the specification of which is estimated using (18), features investment as a ratio of the capital stock varying positively with the profit share as a measure of profitability, the rate of capacity utilization as an accelerator effect, and the ratio of capacity output to capital as a measure of capital productivity at full capacity utilization, which can be seen as a technological factor.

Table 5: Foley-Michl investment function

	(1) Pooled OLS	**(2) Fixed Effect**	**(3) System GMM**(2)
1 Lag of dep. var.(1)	**0.432*** **	**0.250*** **	0.251***
	(0.036)	(0.038)	(0.048)
Profit share	-0.121	-0.191*	**-0.124**
	(0.098)	(0.106)	(0.170)
Capacity utilization	0.518***	0.487***	**0.435*** **
	(0.192)	(0.183)	(0.156)
Capacity-capital ratio	0.495	0.357	**0.301**
	(0.328)	(0.325)	(0.452)
Sectoral growth	0.506***	0.413**	0.585***
	(0.165)	(0.173)	(0.163)
2 Lags of profit share, capacity utilization and capacity-capital ratio	Y	Y	Y
Groups	-	107	107
Observations	1,902	1,902	1,902
Hansen test of joint validity (*p*-value)(3)	-	-	0.645
Difference-in-Hansen (*p*-value)(4)	-	-	0.447
AR2 (*p*-value)(5)	-	-	0.749
Year fixed effects	Y	Y	Y
Industry fixed effects	N	Y	Y
Regressors treated as (6)	-	-	PD
		Long-run Multiplier(7)	
Profit share	0.178	-0.245	**-0.330**
	(0.168)	(0.185)	(0,322)
Capacity utilization	0.705	0.318	**0.581***
	(0.524)	(0.295)	(0.319)
Capacity-capital ratio	0.423***	1.363***	**1.140*** **
	(0.061)	(0.115)	(0.173)

Notes: Same as in Tables 2, 3 and 4.

As also obtained for the Basu-Vasudevan and the Bhaduri-Marglin investment functions, capital accumulation is found to vary negatively with the profit share. However, this result is not statistically significant for all specifications. As regards the rate of capacity utilization, we find that it has a positive and statistically significant contemporary impact on investment behavior in all specifications. For the system GMM estimator, the respective multiplier is 0.435, so that a 1.0% increase in capacity utilization would lead to a 0.44% increase in capital accumulation in the short run. This result is qualitatively similar to that obtained for the Bhaduri-Marglin capital accumulation function. Also for the system GMM estimator, capacity utilization has a statistically significant (at 10% confidence level) effect on investment in the long run. Meanwhile, we find that the ratio of capacity output to capital has a positive and statistically significant long-run (but not contemporary) impact on investment in all specifications, as suggested in Figure 2(c). In fact, for the system GMM estimator, the long-run multiplier is 1.140. It follows that a 1.0% increase in the ratio of capacity output to capital as a measure of capital productivity at full capacity utilization would lead to a 1.14% increase in capital accumulation in the long run. As for the robustness of these results, the Hansen test and the Difference-in-Hansen test corroborate the joint validity of the instruments, the Difference-in-Hansen test on the exogeneity of instruments confirms the soundness of treating the regressors as predetermined, and the autocorrelation test allows the acceptance of the hypothesis of non-autocorrelation in the residuals.

5. Conclusions

There is evidence of a high positive correlation between the profit rate and investment behavior in the Brazilian industrial sector in the last few decades. Against this backdrop, we explore the short- and long-run causal effects of the profit rate and its components (profit share, output-capital ratio, capacity-capital ratio, and capacity utilization) on the flow of investment as a ratio of the capital stock (or rate of capital accumulation) in the Brazilian industrial sector in the 1996-2017 period.

We employ three-digit industrial data which are analyzed using linear dynamic panel data models. At high levels of confidence, the statistically significant results from estimating different specifications of the physical capital accumulation function are the following. First, the profit rate has both short- and long-run positive effects on industrial investment as a ratio of the capital stock. Second, regarding the components of the profit rate, industrial investment as a ratio of the capital stock is positively affected by the ratio of output to capital and the rate of capacity utilization (ratio of actual output to capacity output) in the short and long run and positively impacted by the ratio of capacity output to capital only in the long run. Finally, industrial investment as a ratio of the capital stock is not impacted by the profit share in either the short or long run.

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Appendix

Table A1: PIA-Company (PIA-EMPRESA) two digit – CNAE 2.0: 1996-2007.

CNAE 2.0	Sectors	Companies	Value of industrial transformation - VIT	% VIT by sector	% VIT accumulated
15	Manufacture of food products and beverages	3,093.00	82,100,000.00	16%	16%
24	Manufacture of chemicals	1,305.00	59,000,000.00	12%	28%
34	Manufacture and assembly of motor vehicles, trailers, and bodies	825.00	39,300,000.00	8%	36%
23	Coke manufacturing, oil refining, nuclear fuel production and alcohol production	223.00	65,200,000.00	13%	49%
27	Basic metallurgy	528.00	36,100,000.00	7%	56%
29	Manufacture of machinery and equipment	1,879.00	28,700,000.00	6%	62%
25	Manufacture of rubber and plastic products	1,575.00	17,400,000.00	3%	66%
21	Manufacture of cellulose, paper, and paper products	708.00	19,600,000.00	4%	69%
32	Manufacture of electronic equipment and communications devices and equipment	280.00	13,500,000.00	3%	72%
26	Manufacture of non-metallic mineral products	1,688.00	17,000,000.00	3%	76%
28	Manufacture of metal products - excluding machinery and equipment	1,823.00	14,400,000.00	3%	78%
17	Manufacture of textile products	1,174.00	12,200,000.00	2%	81%
31	Manufacture of electrical machinery, apparatus, and materials	652.00	12,200,000.00	2%	83%
22	Editing, printing and playback of recordings	855.00	16,700,000.00	3%	87%
19	Preparation of leathers and manufacture of leather goods, travel goods and footwear	1,282.00	9,054,866.00	2%	88%
35	Manufacture of other transport equipment	198.00	8,420,903.00	2%	90%
13	Extraction of metallic minerals	74.00	12,300,000.00	2%	93%
36	Manufacture of furniture and various industries	1,740.00	8,300,022.00	2%	94%
18	Manufacture of clothing and accessories	2,581.00	6,924,452.00	1%	96%
20	Manufacture of wood products	1,198.00	5,815,944.00	1%	97%
30	Manufacture of office machinery and computer equipment	92.00	3,550,109.00	1%	98%
16	Manufacture of tobacco products	28.00	4,471,543.00	1%	98%
33	Manufacture of medical and hospital instrumentation equipment	304.00	3,769,610.00	1%	99%
14	Extraction of non-metallic minerals	527.00	2,317,938.00	0%	100%
11	Oil extraction and related services	8.00	1,062,522.00	0%	100%
10	Extraction of mineral coal	15.00	346,133.10	0%	100%
37	Recycling	15.00	230,244.70	0%	100%
		24,670.00	**499,964,286.80**	**100%**	**-**

Source: Elaborated by the authors with data from PIA-Company.

Table A2: PIA-Company (PIA-EMPRESA) two digit – CNAE2.0: 2007-2017.

CNAE 2.0	Sectors	Companies	Value of industrial transformation - VIT	% VIT by sector	% VIT accumulated
10	Manufacture of food products	3,479.00	173,000,000.00	16%	16%
29	Manufacture and assembly of motor vehicles, trailers and bodies	1,090.00	98,000,000.00	9%	25%
19	Coke manufacturing, oil refining, nuclear fuel production and alcohol production	203.00	172,000,000.00	16%	40%
20	Manufacture of chemicals	1,387.00	81,400,000.00	7%	47%
24	Basic metallurgy	724.00	64,000,000.00	6%	53%
28	Manufacture of machinery and equipment	1,990.00	45,700,000.00	4%	57%
22	Manufacture of rubber and plastic products	2,292.00	35,500,000.00	3%	61%
26	Manufacture of computer equipment, electronic and optical products	672.00	26,700,000.00	2%	63%
7	Extraction of metallic minerals	66.00	60,900,000.00	6%	68%
17	Manufacture of cellulose, paper, and paper products	935.00	37,200,000.00	3%	72%
23	Manufacture of non-metallic mineral products	2,225.00	35,000,000.00	3%	75%
27	Manufacture of electrical machinery, apparatus, and materials	813.00	29,400,000.00	3%	78%
25	Manufacture of metal products - excluding machinery and equipment	2,837.00	31,900,000.00	3%	81%
11	Beverage Manufacturing	391.00	37,900,000.00	3%	84%
30	Manufacture of transport equipment, except automotive vehicles	234.00	18,400,000.00	2%	86%
21	Manufacture of pharmaceutical chemicals and pharmaceutical products	293.00	26,700,000.00	2%	88%
13	Manufacture of textile products	1,466.00	17,000,000.00	2%	90%
14	Manufacture of clothing and accessories	4,110.00	18,300,000.00	2%	91%
15	Preparation of leathers and manufacture of leather goods, travel goods and footwear	2,138.00	14,100,000.00	1%	93%
31	Furniture manufacturing	1,436.00	11,200,000.00	1%	94%
16	Manufacture of wood products	1,476.00	9,716,547.00	1%	94%
33	Maintenance, repair and installation of machinery and equipment	594.00	11,000,000.00	1%	95%
32	Manufacture of various products	829.00	10,300,000.00	1%	96%
12	Manufacture of tobacco products	35.00	7,485,086.00	1%	97%
6	Extraction of oil and natural gas	8.00	9,332,419.00	1%	98%
18	Printing and playback of recordings	538.00	7,433,048.00	1%	99%
9	Support activities for mineral extraction	40.00	8,965,709.00	1%	99%
8	Extraction of non-metallic minerals	494.00	6,582,361.00	1%	100%
5	Extraction of mineral coal	13.00	685,382.70	0%	100%
		32,808.00	**1,105,800,552.70**	**1.00**	**-**

Source: Elaborated by the authors with data from PIA-Company (PIA-EMPRESA).

Table A3: Unit root test on panels

	Investment	**Profit rate**	**Profit share**	**Capacity utilization**	**Capacity-capital ratio**	**Output-capital ratio**	**Sectoral growth**
Inverse chi-square	525.70***	313.72***	423.71***	1373.98***	705.00***	734.72***	1594.75***
Inverse logit	-21.31***	-3.28***	-8.83***	-36.31***	-17.06***	-19.14***	-42.31***
Inverse normal	-19.72***	-2.86***	-8.36***	-28.18***	-14.38***	-18.21***	-31.19***
Modified inverse chi-square	29.25***	4.82***	10.14***	56.07***	23.73***	25.17***	66.74***
Panel means	Included	Included	Included	Included	Included	Included	Included
Time trend	Not included	Included	Included	Included	Not included	Not included	Included
Drift term	Included	Not included	Not included	Not included	Included	Included	Not included
ADF regressions	0 lags	0 lags	0 lags	0 lags	0 lags	1 lag	0 lags
Groups	107	108	108	108	108	108	108
Average number of periods	19.68	21.27	21.27	21.30	21.39	21.29	20.36

Source: Annual Industrial Survey - Company (PIA-EMPRESA), see Tables 101 to 106. Trimmed distribution. *Notes*: (1) the null hypothesis is that all panels contain unit roots and the alternative hypothesis is that at least one panel is stationary; and (2) Levels of significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.