



RESEARCH ARTICLE

Capacity utilization under credit constraints: A firm-level study of Latin American manufacturing

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Abstract

In developing countries, the credit market usually is underdeveloped. Low access to credit affects firms' production decisions and restrains them from optimizing inputs to achieve the maximum output. This article examines the link between credit constraints and capacity utilization and whether it varies across manufacturing subsectors. The sample consists of 4,790 private manufacturing firms in six Latin-American countries. The endogenous switching model is applied to control for endogeneity between credit constraint conditions and capacity utilization and heterogeneity between credit-constrained and credit-unconstrained firms. The counterfactual analysis based on the estimation results suggests that constrained firms would have seen an increase of 26.8% capacity utilization had they not been constrained and unconstrained firms a decrease of 23.7% capacity utilization had they been constrained. Credit constraints generally affect medium-high-tech firms more severely than low-tech firms. The counterfactual analysis further reveals that, for credit-constrained high technology firms, depressed outputs are primarily related to labor productivity rather than capital productivity.

KEYWORDS

capacity utilization, credit constraints, endogenous switching model, Latin America

1 | INTRODUCTION

Manufacturing-led development has proven to be a successful development strategy because of the manufacturing sector's direct contribution to economic growth, spillover effect, and dynamic productivity gains in terms of scale, tradability, and job creation (Felipe, Mehta, & Rhee, 2018; Hallward-Driemeier & Nayyar, 2017; Haraguchi, 2015). According to Kaldor's law (Kaldor, 1966), the productivity of nonindustrial sectors depends largely on growth in the manufacturing sector. For developing countries, manufacturing development is

accompanied by upgrading processes and structural changes in this sector (Haraguchi, 2015). The industry updating process, regarded as an effective practice for catching up to current technological frontiers, relies on new investment. The formation of new investment is further related to capacity utilization. Highly efficient utilization of capital and lower spare capacity lead to an increase in depreciation rates and stimulate the substitution of old facilities for new ones (Greenwood, Hercowitz, & Huffman, 1988; Liu & Wang, 2014; Melitz, 2003). However, credit markets are normally underdeveloped in developing countries where firms are typically

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constrained by limited financial resources, which prevents them (especially private firms) from undertaking value-enhancing investments and upgrading their existing facilities to enhance productivity (Almeida, Campello, & Weisbach, 2004; Bellone, Musso, Nesta, & Schiavo, 2010; Chen, Hua, & Boateng, 2017). According to the World Bank Enterprise Surveys, the biggest obstacle faced by 140,619 private firms in 142 developing countries between 2008 and 2019 was limited access to credit, followed by corruption.

Existing literature has widely investigated the impact of credit constraints on firm performance and operational decisions, especially regarding exporting propensity, investment decisions, and the choice of production technologies (Bellone et al., 2010; Hasan & Sheldon, 2016; Lashitew, 2017; Sasidharan, Lukose, & Komera, 2015). The effects of credit constraints may act through capacity utilization to impact firms' operations and investment decisions. For example, given capital stock and productivity levels, firms with a high rate of capacity utilization are more likely to enter into the global market (Tian, 2016). Capacity utilization affects firms' decisions to export, invest, and hire employees, which further determine economic development in developing countries. How financial status affects capacity utilization provides fundamental explanations of firms' behavior when they face binding credit constraints. This study is first motivated by the absence of research on the impact of credit constraints on capacity utilization.

There are significant differences in the capital structures of manufacturing subsectors, exemplifying the fact that a firm's debt ratio depends on the industry in which it operates (Talberg, Winge, Frydenberg, & Westgaard, 2008). Manufacturing subsectors further differ from each other regarding capital expenditures, the share of tangible assets out of total assets, and the availability of trade credit, which affects their demand for external financing (Chor & Manova, 2012). Credit constraint conditions may have differential effects on tangible and intangible capital and human capital, which are inputs of capacity utilization and play a different role in capacity utilization, depending on the types of manufacturing subsectors. For example, in the short run, labor productivity is more vulnerable when a firm faces credit constraints, since labor input generally responds directly and instantly to financial friction than physical capital. Above all, heterogeneity across manufacturing subsectors may influence the relationship between credit constraints and capacity utilization for these subsectors.

The purpose of this article is to explore the impact of credit constraints on capacity utilization and whether the link between credit constraints and capacity utilization varies across manufacturing subsectors. The share of a firm's actual output out of its maximum output with all

needed resources available serves as a measure of capacity utilization. Since capacity utilization refers to output, credit constraints on capacity utilization may work through the impact on inputs, such as labor and capital. Greenwood et al. (1988) incorporated a variable of capital utilization into the standard neoclassical production function and revealed a positive link between capacity utilization and capital/labor productivities. Credit constraints may restrain firms' ability from optimizing the use of capital and labor, which leads to lower capacity utilization in terms of output (Ahn & McQuoid, 2017). We further investigated how credit constraints influence capital productivity and labor productivity, the channel through which credit constraints affect capacity utilization.

The case study in this article is composed of data on private manufacturing firms in six Latin-American countries: Argentina, Bolivia, Ecuador, Paraguay, Peru, and Uruguay. These sample countries are in the same region and share similarities in terms of their history and economic conditions, although they differ in levels of development, the composition of the manufacturing industry, and the liberalizing of internal and external financing. The sample countries are generally ranked as developing and emerging industrial economies, with Argentina and Uruguay as emerging industrial economies and Bolivia, Ecuador, Paraguay, and Peru as developing economies (UNIDO, 2017). They also fall into large countries (Argentina and Peru) and medium-sized countries (Bolivia, Ecuador, Paraguay, and Uruguay).

The research purpose is fulfilled by using an endogenous switching model composed of one regression equation for credit constraint conditions and two regression equations for capacity utilization conditional on firms' credit constraint conditions. The endogenous switching model first controls for endogeneity between credit constraint conditions and capacity utilization, possibly arising from unobserved factors influencing the two variables. In addition, the separate regression equations of capacity utilization for credit-constrained and credit-unconstrained firms control for heterogeneity in the two firm groups. Given significant covariances between credit constraint conditions and capacity utilization, the counterfactual analysis is applied to quantify the impact of credit constraints on capacity utilization. The estimation results first confirm the endogeneity between credit constraint conditions and capacity utilization. Compared with low-tech (LT) firms, high technology manufacturing firms are less likely constrained by external financing, all other things being equal. Neither constrained nor unconstrained high-tech firms have higher capacity utilization than corresponding LT firms. However, the counterfactual effects on capacity utilization (from constrained to unconstrained, or vice versa) are generally

higher for high-tech firms than for LT firms. This is primarily due to labor productivity rather than capital productivity, as evidenced by the empirical findings.

The structure of the article is as follows. In Section 2, we discuss credit constraints and capacity utilization in developing countries and present the hypotheses. In Section 3, we describe the data and provide measures for credit constraints and capacity utilization. Section 4 details the modeling strategy and specifies the empirical models. The evidence from statistical and econometric analyses is then presented in Section 5. Section 6 investigates the robustness of the empirical findings and provides additional econometric evidence. Finally, we summarize the main findings and implications of this study in Section 7.

2 | CONTEXT AND HYPOTHESES

A well-developed financial market more effectively allocates capital to firms with high-value projects, which in turn promotes economic growth (Fisman & Love, 2003). Manufacturing firms in developing countries are, however, often constrained by limited financial resources. A productive firm facing credit constraints likely experiences amplified negative consequences with lower equity value, which further results in a reallocation of resources from productive to unproductive firms (Liu & Wang, 2014). As noted by Pietrobelli and Rabellotti (2005), most Latin-American countries are constrained by limited financial resources needed to upgrade the manufacturing sector. This is reflected in the developing strategies applied by these countries. In terms of the application of digital technologies, this region greatly lags behind developed countries (Dutz, Almeida, & Packard, 2018). Countries in this region have instead specialized in natural resource-based sectors (e.g., copper, marble, and fruit), since less capital investment is required in these sectors compared with other industries (Braun, Briones, & Islas, 2019; Giuliani, Pietrobelli, & Rabellotti, 2005; Katz, 2001).

For developing countries, the process of upgrading the manufacturing sector is subject to technology diffusion, labor market policies, and product market policies (Dutz et al., 2018; Giuliani et al., 2005). Upgrading processes in manufacturing subsectors leads to a sound industry structure, which is crucial for growth and development in developing countries. Updating the manufacturing industry means replacing old equipment with new equipment. A high level of capital utilization and hence a high rate of capacity utilization accelerate the depreciation of old equipment and stimulate the formation of the new investment, indicating that capital utilization interacts with investment shocks and affects

firm productivity and employment (Greenwood et al., 1988). In terms of adopting new technologies such as digitalizing, there is high heterogeneity across Latin-American countries, which is further reflected in differences in firm productivity and economic growth (Dutz et al., 2018).

A number of articles have investigated how capacity utilization affects macroeconomic indicators such as the distribution of income, the ratio of savings to investment, inflation rate, and productivity movements (Nikiforos & Foley, 2012; Schoder, 2014; Segerson & Squires, 1993). Using aggregate data, Nikiforos and Foley (2012) examined the causal relationship between capacity utilization and income distribution. Other than on a macro level, capacity utilization directly affects firms' investment decisions, employment, and export propensity (Melitz, 2003; Tian, 2016). Given the critical role that capacity utilization plays in the macroeconomic indicators and firm performance, it is important to explore the drivers underlying capacity utilization across business sectors. The rate of capital utilization is a consequence of firms' investment decisions and demand uncertainty (Nikiforos & Foley, 2012). Firms facing financial constraints have more difficulty executing investment decisions and have a limited ability to choose an optimal level of capacity utilization (Ahn & McQuoid, 2017). Bresnahan and Ramey (1993) estimated the capacity equation using monthly data on the U.S. automobile industry and found a significant impact of demand shift on capacity utilization. In addition to the demand shift, the physical and financial constraints that firms face block them from achieving their maximum output (Ahn & McQuoid, 2017). Thus, we hypothesize that financial constraints lead to a low capacity utilization. In other words, firms have a limited ability to target an optimal rate of capacity utilization when they face binding credit constraints.

External financial dependence varies across manufacturing subsectors, affecting credit demand (Manova, 2013). High-tech firms are ordinarily small, young, and experienced rapid growth, which affects their demand for external financing and their loan applications (Farre-Mensa & Ljunqvist, 2016). Facing credit constraints, some firms may build a secure connection with banks and hence have better access to credit (Braun et al., 2019). In developing countries, one essential element of product market policies is the availability of bank loans to firms for value-enhancing activities. Policymakers in Latin America as well as other developing countries facilitate the development of enterprises through tax advantages, preferential allocations of necessary inputs, and credits (Comeau, 2003). Governmental credit programs deter poorly developed financial markets and promote the potential availability of external financing, which leads to high economic activity and growth (Bigsten et al., 2003;

Fauceglia, 2015). During the last decade in Latin America as a whole, improved macroeconomic policies, banking, and other financial institutions have led to strong economic performance (Ocampo, Bastian, & Reis, 2018). Above all, we hypothesize that, due to their different levels of external financial dependence and external credit supply (from financial institutions or government credit programs), the probability of firms being constrained by access to finance varies across manufacturing subsectors in which firms operate. As we discussed above, capacity utilization depends on capital and labor inputs, which respond to financial friction in different ways. For example, credit-constrained firms tend to replace intangible asset investment with physical assets, which are pledged as collateral required by banks. Since the role of various assets and human capital in capacity utilization depends on the types of manufacturing subsectors, the relationship between credit constraints and capacity utilization may differ in various manufacturing subsectors.

Lower capacity utilization indicates that firms are not effectively allocating capital and labor inputs in production. In general, firms with low access to finance cannot optimize their investments, indicating a negative relationship between credit constraints and productivity (Ganau, 2016). Downtime or facility maintenance activities reduce the share of labor working directly on production. Lower labor productivity can be a result of lower labor force skills (Crafts & Milles, 2013). A recent study by Li, Liao, and Zhao (2018) provided evidence for the effect of credit constraints on firm labor productivity. On the other hand, credit constraints may distort firms' asset composition toward tangible assets at the expense of intangible assets, which reduces capital productivity. Labor productivity and capital utilization are interdependent (Greenwood et al., 1988), which jointly determine the level of capacity utilization. The empirical issue is how credit constraints affect capacity utilization through the impacts on capital productivity and labor productivity and whether the mechanism varies across manufacturing subsectors.

3 | DATA AND DEFINITIONS

3.1 | Data sources

This article uses a rich database collected by the World Bank Enterprise Surveys in 2006, 2010, and 2017 for six Latin-American countries (Enterprise Surveys, 2017) to examine the impact of credit constraints on capacity utilization. The surveys employ a stratified sampling methodology (citing variables of firm size, sector, and geographic region within a country) to collect private firm data on the business environment in developing countries (see <https://www.enterprisesurveys.org/en/enterprisesurveys>

for methodological information). The sample firms are chosen randomly within each stratifying variable. The standardized stratified sampling methodology and the detailed quantitative and qualitative questions about firms' access to finance allow for better comparisons of the impact of credit constraints on capacity utilization across economic sectors in developing countries. The data have been widely used in the literature to explore business environments in general and credit constraints in particular (Deininger & Mpuga, 2005; Hansen & Rand, 2014; Hasan & Sheldon, 2016; Kenny, 2009; Krkoska & Robeck, 2008; Zhang, 2019; Zhang & Xie, 2020).

The full sample consists of 6,814 observations (manufacturing firm-years). After excluding the missing observations for unreported, negative, or zero income (and cost), 4,806 observations remain. Of these, 16 are high-tech firms in the precision instruments industry, mostly located in Argentina. We omitted these high-tech firms to ensure comparability between different manufacturing subsectors, resulting in a final tally of 4,790 observations for analysis. The sample firms fall into three categories according to their technological levels (OECD, 2011; UNIDO, 2017): LT, medium-low-tech (MLT), and medium-high-tech (MHT) firms. We further separated LT firms in the dominant industries (food, textiles, and garments) from other LT firms and treated them as individual sectors. Table 1 presents sample distribution by country and the technological level.

As shown in Table 1, other LT firms account for 9.31% of the entire sample. The food sector is the largest individual subsector with a share of 27.7% of the entire sample, followed by garments and textiles industries (17.0% and 8.60%, respectively). MLT firms account for 15.1% of the whole sample, while MHT firms represent 22.3%. Argentina and Peru have the largest number of firms in the dataset (1,654 and 1,357, respectively), followed by four other countries with firm numbers ranging from 518 to 385. Since the surveys are based on a stratified sampling methodology, the sample distribution reflects the greater economic size of Argentina and Peru relative to their four neighboring countries. However, economic size does not directly relate to industry composition for these sample countries. The share of MLT and MHT firms of a country's total surveyed firms is 41.3% for Argentina and 38.0% for Peru, which are close to the Paraguayan counterpart (39.9%). For Paraguay, a great share of manufacturing value-added was from the MLT and MHT sectors (UNIDO, 2017).

3.2 | Identifying credit-constrained firms

Since credit constraints are not directly observable, researchers rely on various indirect measures as a proxy

TABLE 1 Distribution of firms across manufacturing sectors, by country

| ISIC | Manufacturing sectors | Argentina | Bolivia | Ecuador | Paraguay | Peru | Uruguay | Total |
|----------------------|--|-----------|---------|---------|----------|-------|---------|-------|
| Low-tech (LT): Other | | | | | | | | |
| 16 | Tobacco | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| 19 | Leather | 32 | 2 | 3 | 1 | 29 | 13 | 80 |
| 20 | Wood | 9 | 4 | 6 | 1 | 3 | 5 | 28 |
| 21 | Article | 18 | 1 | 4 | 4 | 11 | 8 | 46 |
| 22 | Publishing, printing, and recorded media | 25 | 10 | 8 | 12 | 30 | 8 | 93 |
| 36 | Furniture | 8 | 2 | 0 | 4 | 23 | 2 | 39 |
| 37 | Recycling | 2 | 0 | 1 | 0 | 1 | 1 | 5 |
| 99 | Other manufacturing | 0 | 32 | 81 | 41 | 0 | 0 | 154 |
| | Subtotal | 94 | 51 | 103 | 63 | 97 | 38 | 446 |
| 15 | LT: Food | 454 | 124 | 121 | 103 | 355 | 168 | 1,325 |
| 17 | LT: Textiles | 185 | 11 | 34 | 7 | 117 | 58 | 412 |
| 18 | LT: Garments | 238 | 96 | 65 | 68 | 272 | 75 | 814 |
| | Subtotal (LT firms) | 971 | 282 | 323 | 241 | 841 | 339 | 2,997 |
| Medium-low-tech | | | | | | | | |
| 23 | Refined petroleum product | 3 | 0 | 0 | 0 | 0 | 0 | 3 |
| 25 | Plastics and rubber | 74 | 10 | 19 | 14 | 67 | 49 | 233 |
| 26 | Nonmetallic mineral products | 21 | 21 | 9 | 32 | 22 | 9 | 114 |
| 27 | Basic metals | 10 | 2 | 0 | 1 | 15 | 3 | 31 |
| 28 | Fabricated metal products | 139 | 14 | 23 | 9 | 148 | 10 | 343 |
| | Subtotal | 247 | 47 | 51 | 56 | 252 | 71 | 724 |
| Medium-high-tech | | | | | | | | |
| 24 | Chemicals | 172 | 49 | 91 | 95 | 191 | 100 | 698 |
| 29–30 | Machinery and equipment | 219 | 3 | 6 | 5 | 35 | 1 | 269 |
| 31–32 | Electronics | 18 | 3 | 1 | 3 | 19 | 0 | 44 |
| 34–35 | Transport machines | 27 | 1 | 3 | 1 | 19 | 7 | 58 |
| | Subtotal | 436 | 56 | 101 | 104 | 264 | 108 | 1,069 |
| | Total | 1,654 | 385 | 475 | 401 | 1,357 | 518 | 4,790 |

Note: ISIC denotes the International Standard Industrial Classification of All Economic Activities.

for credit constraints (Wagner, 2014; Farre-Mensa & Ljungqvist, 2016; Alm, Liu, & Zhang, 2019). This study uses loan applications (i.e., demand for external financing) and the results of loan applications to measure credit constraints. Conditional on credit demand, the rejection of an application implies credit constraints faced by firms (Bigsten et al., 2003; Hansen & Rand, 2014). The relevant questions in the questionnaires are: “Referring to the last fiscal year, did the establishment apply for lines of credit or loans?” “What were the main reasons why this establishment did not apply for any line for credit or loan?” and “Does establishment have a line of credit or loan from a financial institution?”

Firms are credit constrained if they (a) applied for a loan in the fiscal year but did not have a line of credit or

loan at the time of interview, or (b) did not apply for a loan for the reason of “Application procedures were complex,” “Collateral requirements were too high,” or “Size of loan and maturity were insufficient.” Firms are not treated as credit constrained if they did not apply for a loan for the reasons of “Interest rates were not favorable” and “Did not think it would be approved,” which may reflect a low return of investment relative to interest rates and hence no demand for external funds. This taxonomy is consistent with the one proposed by Bigsten et al. (2003), Hansen and Rand (2014), and Wellalage and Locke (2016), with the exception of outcomes of loan applications. The literature uses the outcome of the most recent application for a line of credit or loan to identify the presence of credit constraints. Of the three waves

used in this study, only the most recent one includes a question about the outcome of loan applications. Given that the maturity of a recently approved loan is longer than 1 year, a firm without a line of credit or loan at the end of the fiscal year indicates the rejection of a recent loan application. Therefore, our definition of the constraint measure is not fundamentally different from the one used in previous studies.

3.3 | Measuring capacity utilization

Capacity utilization (“*CU*”) is based on the following question in the questionnaire: “What was this establishment’s current output in comparison with the maximum output using its facilities at the time?” This is expressed as:

$$CU = \frac{y}{y^*} \quad (1)$$

where y is the current output and y^* is the maximum output. This definition of capacity utilization is close to the one used in the literature. For example, Nikiforos and Foley (2012) defined capacity utilization as the ratio of output to potential output, using quarterly data from the U.S. Bureau of Economic Analysis. The Enterprise Surveys leave the definition of maximum output to respondents. Some surveys ask firms: “What was this establishment’s output produced as a proportion of the maximum output possible with all resources available?” The U.S. Bureau of Economic Analysis respondents report their maximum output (full production capacity) based on the assumption that only the machinery and equipment currently in place and ready to operate be utilized, including normal downtime, maintenance, repair, and cleanup, and that labor, materials, and utilities are fully available (Morin & Stevens, 2005). Firms likely consider these points when assessing their maximum output and reporting their rate of capacity utilization in the Enterprise Surveys.

Equation (1) measures capacity utilization regarding output. The other measurement of capacity utilization is the level of facility (capital) utilization, as shown in Greenwood et al. (1988):

$$y = G(kh, l) \quad (2)$$

where $G(\cdot)$ is the production function, k is the capital stock, h represents the utilization rate of k , and l is labor input. When h equals unity and represents a full utilization of facilities, Equation (2) equals the maximum output, y^* . This indicates that we can rewrite Equation (1) as:

$$CU = \frac{G(kh, l)}{G(k, l)} \quad (3)$$

The level of capacity utilization depends on capital utilization (h), which is further subject to the age of the machinery and equipment in place, downtime, maintenance, and normal repair. These factors are all affected by liquidity and financial conditions. On the other hand, h may reflect the portion of the total labor directly involved in the production, with the remainder working on maintenance activities or on hold due to downtime (Greenwood et al., 1988).

3.4 | Capacity utilization and credit constraints

We report average capacity utilization by industry sector for firms classified as either credit constrained or unconstrained (Table 2). We ask whether the observed capacity utilization ratios differ between constrained and unconstrained firms, for the whole sample and the subsectors.

In this region, 40.9% of the manufacturing firms are constrained by access to external credit. As a whole, unconstrained firms have a higher level of capacity utilization than constrained firms, 72.5% versus 68.1%. This indicates a negative relationship between credit constraints and capacity utilization. For subsectors, MLT firms are less constrained by access to external liquidity, with a share of constrained firms at 37.0%. Other subsectors see a share of constrained firms ranging between 41.3% and 42.6%. Constrained firms in the subsectors generally have lower capacity utilization than unconstrained firms; however, the difference between the rates of capacity utilization for constrained and unconstrained firms varies. The other LT firms are less affected by access to external financing since the capacity utilization of constrained firms is only 2.45% less than the counterpart for unconstrained firms. Capacity utilization in the textile subsector is 67.3% for constrained firms and 73.1% for unconstrained firms, indicating the sensitivity of capacity utilization to financial friction.

4 | ECONOMETRIC MODEL

Firms that face financing constraints cannot fully utilize their capacity to reach maximum output. An optimized rate of capacity utilization reflects the availability of financial resources, among other resources. Observable factors such as firm size and firm age may affect both the demand for credit and the actual output. On the other

TABLE 2 Sample distribution and capacity utilization (in %), by industry sector and financial status

| Sector | Number of | | Capacity utilization (%) of | |
|----------------------|-------------------|---------------------|-----------------------------|---------------------|
| | Constrained firms | Unconstrained firms | Constrained firms | Unconstrained firms |
| Low-tech (LT): Other | 190 | 256 | 66.0 | 68.4 |
| LT: Food | 556 | 769 | 69.0 | 72.7 |
| LT: Garments | 170 | 242 | 67.3 | 73.1 |
| LT: Textiles | 342 | 472 | 69.2 | 74.1 |
| Medium-low-tech | 268 | 456 | 66.7 | 71.6 |
| Medium-high-tech | 433 | 636 | 68.3 | 73.1 |
| Total | 1,959 | 2,831 | 68.1 | 72.5 |

hand, there are probably unobserved variables (e.g., macroeconomic cycle, business environment, industry development, and business cycle) that affect both a firm's access to external funds and the realized capacity utilization, indicating an endogeneity issue. In that case, the estimators from a model using a dummy variable to catch the impact of credit constraints on capacity utilization in the pooled sample are not consistent. An endogenous switching model corrects for sample section bias due to unobserved factors that affect both credit constraint conditions and capacity utilization (Maddala, 1983). The endogenous switching model has recently been applied to examine the impact of credit rationing on the efficiency of agricultural production (Ali, Deininger, & Duponchel, 2014), to test how credit constraints affect agricultural productivity and rural household income (Dong et al., 2012) and to explore economic returns to government-funded extension programs (Läpple, Hennessy, & Newman, 2013). Another advantage of this model is that the parameters of credit-constrained firms and credit-unconstrained firms are estimated separately, thus controlling for heterogeneity between the two firm groups. Accordingly, in this study, the endogenous switching model was applied.

4.1 | Econometric specification

The endogenous switching model is composed of joint estimations of the probability of being constrained (in the first stage) and capacity utilization (in the second stage). In the first stage, a probit model is applied to estimate the likelihood of firms being constrained in the financial market. In the second stage, separate regression equations are used to model capacity utilization conditional on credit constraint conditions. The probit model used in the first stage is specified as:

$$C_i^* = \delta' \mathbf{Z}_i + u_i \quad (4)$$

$$C_i = \begin{cases} 1 & \text{iff } C_i^* > 0 \\ 0 & \text{iff } C_i^* \leq 0 \end{cases} \quad (5)$$

where C^* is a latent variable that captures the expected results of being constrained by access to external financing. C equals one if a firm is constrained (and hence $C^* > 0$) and takes zero otherwise. \mathbf{Z} represents a vector of explanatory variables that determines firms' credit constraint conditions.

In the second stage, capacity utilization for constrained and unconstrained firms is modeled by two separate regression equations in the reduced form:

$$Y_{1i} = \beta_1' \mathbf{X}_{1i} + \varepsilon_{1i} \text{ iff } C_i = 1 \quad (6a)$$

$$Y_{2i} = \beta_2' \mathbf{X}_{2i} + \varepsilon_{2i} \text{ iff } C_i = 0 \quad (6b)$$

where Y_1 and Y_2 represent capacity utilization for credit-constrained and credit-unconstrained firms, respectively. \mathbf{X} is a vector of explanatory variables that affect the level of capacity utilization. Most variables in \mathbf{Z} may also affect the level of capacity utilization. However, some variables in \mathbf{Z} work as identifying instruments and hence do not have a direct impact on capacity utilization level.

The system equations are estimated by construction through a logarithmic likelihood function with respect to the distribution of the error terms in (4), (6a), and (6b), which is:

$$\Omega = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{2u} \\ \sigma_{1u} & \sigma_1^2 & \cdot \\ \sigma_{2u} & \cdot & \sigma_2^2 \end{bmatrix} \quad (7)$$

where σ_u^2 , σ_1^2 , and σ_2^2 are the variances of the error terms in Equations (4), (6a), and (6b), respectively. σ_{1u} and σ_{2u} are the covariance between the error terms in the credit criterion equation and the respective capacity utilization equation. The covariance between the error terms in the two outcome equations is zero, since Y_1 and Y_2 are never observed simultaneously for a given firm. The regression equations are estimated simultaneously by the maximum likelihood function. When estimating the model, σ_u^2 in matrix (7) is set to one and treated as a scale factor.

Using the estimation results from the endogenous switching model, the conditional expectations of the observed capacity utilization for credit-constrained and credit-unconstrained firms are:

$$E(Y_{1i} | C_i = 1, \mathbf{X}_{1i}) = \beta'_1 \mathbf{X}_{1i} + \sigma_1 \rho_1 f(\delta' \mathbf{Z}_i) / F(\delta' \mathbf{Z}_i) \quad (8a)$$

$$E(Y_{2i} | C_i = 0, \mathbf{X}_{2i}) = \beta'_2 \mathbf{X}_{2i} - \sigma_2 \rho_2 f(\delta' \mathbf{Z}_i) / [1 - F(\delta' \mathbf{Z}_i)] \quad (9a)$$

where $f(\cdot)$ is the standard normal probability density function; $F(\cdot)$ is the standard normal cumulative density function; ρ_1 and ρ_2 are the correlation coefficients between the error terms in Equations (4) and (6a), and in Equations (4) and (6b), respectively.

For counterfactual analysis, we calculate the counterfactual expectation for constrained firms if they had not been constrained and for unconstrained firms if they had been constrained:

$$E(Y_{2i} | C_i = 1, \mathbf{X}_{1i}) = \beta'_1 \mathbf{X}_{1i} - \sigma_1 \rho_1 f(\delta' \mathbf{Z}_i) / [1 - F(\delta' \mathbf{Z}_i)] \quad (8b)$$

$$E(Y_{1i} | C_i = 0, \mathbf{X}_{2i}) = \beta'_2 \mathbf{X}_{2i} + \sigma_2 \rho_2 f(\delta' \mathbf{Z}_i) / F(\delta' \mathbf{Z}_i) \quad (9b)$$

The difference between the expectation of the actual capacity utilization and the counterfactual expectation is the treatment effect, that is, the impact of credit constraints on capacity utilization. For example, the difference between (8a) and (8b) is the effect of “treatment” (being constrained) on the capacity utilization of constrained firms. The difference between (9b) and (9a) is the “treatment” effect on capacity utilization for unconstrained firms.

4.2 | Control variables

The survey data include a large number of firm characteristics, which probably affect firms' financial status (Hansen & Rand, 2014; Presbitero, Rabellotti, & Piras,

2014). Firm characteristics are directly related to the need for external financial resources. The information used by firms to decide their demand is likely also used by banks to determine credit supply (Bigsten et al., 2003). The basic firm features such as the number of employees and age directly affect the need for external financing and the inherent riskiness of a loan application (Asiedu, Kalonda-Kanyama, Ndikumana, & Nti-Addae, 2013; Winker, 1999). In terms of firm legal status, shareholding companies are probably less risk-averse and more motivated to undertake value-enhancing investments than firms with a sole proprietorship. Firms that belong to a large establishment may have internal financial resources and lower demand for external financing. Firms partly owned by foreign investors have more financial resources than firms only owned by domestic investors. In addition, firms with informal credit sources and overdrafts may have a lower demand for external financing.

The variables in the regression equation for credit constraint conditions are all supposed to affect capacity utilization. However, for the model to be identified, we need instrument variables that only affect credit constraint conditions. Audited financial statements reduce information asymmetry between firm managers and banks and hence affect loan application outcomes on the supply side. Banks may consider a firm's growth rate when evaluating the default risk of a loan application. Accordingly, a dummy variable set for firms with audited financial statements and sales growth rates coded as quantile dummy variables are hypothesized to be instrument variables.

Demand uncertainty is one of the determinants affecting the rate of capacity utilization and is beyond firms' control (Ahn & McQuoid, 2017). In the survey questionnaire, firms reported the number of competitors their primary products faced in their primary markets. We use this question to create variables that roughly reflect competitive pressures and market uncertainty, since markets with more competitors may result in higher fluctuations for individual firms. An individual dummy is set for firms with “too many competitors to count.” The other firms are categorized into four quantiles (dummies) according to the number of competitors. Nikiforos and Foley (2012) stated that lagged capacity utilization could be treated as a demand shifter. In the survey questionnaire, firms did not report capacity utilization in previous years. They did, however, report sales and the number of employees 2 years prior to the survey year. We divided sales (in U.S. dollars) by the number of full-time employees to obtain lagged labor productivity. The logarithmic lagged labor productivity is incorporated in the outcome equations. Since there is a positive link between labor productivity and capital

productivity, lagged labor productivity is expected to affect capacity utilization directly or indirectly through its correlation with lagged capital productivity.

The list of variables used in the analysis and descriptive statistics are presented in Table 3. For dummy variables, the mean is the share of firms with the characteristics out of the total number of firms. For example, the mean of *Credit-Constraints* is 0.409, indicating that 40.9% of firms are constrained by access to external funding. For firms in the Latin-American region, the average actual output is 70.9% of the maximum output that firms would produce with all resources available.

5 | EMPIRICAL RESULTS

5.1 | Univariate *T*-test results

The endogenous switching model controls for both endogeneity and heterogeneity. We first explore the heterogeneity between the constrained and unconstrained firms using a univariate *T*-test. Table 4 presents the test results and summary statistics of the variables classified by constrained and unconstrained firms.

As discussed earlier, unconstrained firms have a higher level of capacity utilization than constrained firms. Table 4 shows that the difference is statistically significant. The question is whether there are differences in firm characteristics (explanatory variables) between the two firm groups. For firm size, although the share of both medium-sized and large firms differs significantly in the two sample groups, only the share of large firms has a substantial difference (11.8% for constrained firms and 29.0% for unconstrained firms). The share of constrained firms with informal credit sources for both working capital and fixed assets is higher than the corresponding share of unconstrained firms. This is echoed by differences in shares of firms with overdraft facilities. 82.5% of unconstrained firms have an overdraft facility compared with only 53.5% of constrained firms. This also indicates substitutability between informal credit sources and overdraft facilities. The sample distributions by manufacturing subsector are not strongly different for the two subsample groups, noting that only the difference between shares of constrained and unconstrained MHT firms (−2.4%) is statistically significant. Regarding market competition, the share of constrained firms in each high quantile group is smaller than the corresponding share of unconstrained firms. Although a competitive market indicates a high level of demand fluctuation, firms that operate in competitive markets may benefit from strong demand.

5.2 | Estimation results

The parameters of the endogenous switching model are estimated simultaneously using the full information likelihood method based on the distribution of the error terms, thereby generating consistent estimators (Lokshin & Sajaia, 2004). Table 5 presents the estimation results. The last two rows report the estimated correlation coefficients (ρ_1 and ρ_2) and variances (σ_1^2 and σ_2^2), which are all significant. The significant correlation coefficients indicate that some unobserved variables affect both credit constraint conditions and the level of capacity utilization. This further justifies the appropriateness of the model used in the study.

The estimation results of the criterion equation for credit constraint conditions suggest that firms in a large-sized group (in terms of the number of employees) and firms with a fast growth rate of revenue have a lower likelihood of being credit constrained. In general, the level of reduction increases gradually as firms become larger or firms grow faster, indicating a monotonic pattern. While firm age does not affect the probability of being credit constrained, firms led by managers with more experience have a lower probability of being credit constrained. Firms with informal credit sources for fixed assets are more credit constrained; however, access to overdraft financing alleviates credit constraints. All country dummies are significant and negative, indicating that firms in small countries are less credit constrained than firms in the base country of Argentina, due probably to the heterogeneity in the demand and supply of financial markets in these countries. Firms owned partly by foreign investors are more likely to be constrained by credit availability. None of the subsector dummies are significant, indicating that the technological regimes do not affect firms' probability of meeting the credit constraint condition. Thus, we reject the hypothesis that a firm's likelihood of being constrained by access to external financing is related to the manufacturing subsector in which it operates.

Table 5 also presents the *separate* estimation results for the constrained firm group and the unconstrained firm group. Some of the variables that significantly affect the odds of credit constraints also affect capacity utilization for both constrained and unconstrained firms, such as in the case of dummies for informal credit sources for working capital and fixed assets as well as some country dummies. Current levels of capacity utilization are positively associated with previous labor productivity for both constrained and unconstrained firms. However, while constrained firms with informal credit sources for fixed assets have lower capacity utilization, the opposite is true for unconstrained firms. Using informal credit sources to

TABLE 3 Definition of variables and descriptive statistics

| Variable | Definition | Mean | SD |
|------------------------------|---|-------|-------|
| Credit constraint | See text | 0.409 | 0.492 |
| Capacity utilization | Actual output/maximum output, see text | 70.69 | 20.72 |
| Size: Medium | Firms with employees: ≥ 20 and ≤ 99 | 0.355 | 0.479 |
| Size: Large | Firms with employees: ≥ 100 | 0.220 | 0.414 |
| Firm age | Years | 3.047 | 0.805 |
| Manager experience | Years | 2.975 | 0.746 |
| Legal status | Firms with legal status other than sole proprietorship | 0.899 | 0.301 |
| Foreign ownership | Firms with part of ownership by foreign investors | 0.117 | 0.321 |
| Part of larger establishment | Firms under a larger establishment | 0.166 | 0.372 |
| Informal credit sources: WC | Firms using informal credit sources for working capital | 0.195 | 0.396 |
| Informal credit sources: FA | Firms using informal credit sources for fixed assets | 0.357 | 0.479 |
| Overdraft | Firms using overdraft facilities | 0.706 | 0.455 |
| Sector: Food | Firms in food industry | 0.277 | 0.447 |
| Sector: Garments | Firms in garments industry | 0.170 | 0.376 |
| Sector: Textiles | Firms in textile industry | 0.086 | 0.280 |
| Sector: MLT | Medium-low-tech firms | 0.223 | 0.416 |
| Sector: MHT | Medium-high-tech firms | 0.151 | 0.358 |
| Bolivia | Firms in Bolivia | 0.080 | 0.272 |
| Ecuador | Firms in Ecuador | 0.099 | 0.299 |
| Paraguay | Firms in Paraguay | 0.084 | 0.277 |
| Peru | Firms in Peru | 0.283 | 0.451 |
| Uruguay | Firms in Uruguay | 0.108 | 0.311 |
| Year: 2006 | Dummy for 2006 | 0.376 | 0.484 |
| Year: 2010 | Dummy for 2010 | 0.367 | 0.482 |
| Audit | Firms with audited financial reports | 0.508 | 0.500 |
| Growth: Second quantile | Firms in the second quantile by sales growth rate | 0.250 | 0.433 |
| Growth: Third quantile | Firms in the third quantile by sales growth rate | 0.251 | 0.433 |
| Growth: Fourth quantile | Firms in the fourth quantile by sales growth rate | 0.250 | 0.433 |
| Labor productivity, lagged | Sales/number of employees | 10.49 | 4.234 |
| Competitor: Second quantile | Firms in the second quantile by number of competitors in the marked | 0.202 | 0.402 |
| Competitor: Third quantile | Firms in the third quantile by number of competitors in the marked | 0.202 | 0.402 |
| Competitor: Fourth quantile | Firms in the fourth quantile by number of competitors in the marked | 0.202 | 0.402 |
| Competitor: Many | Firms reported "too many competitors to count" | 0.191 | 0.393 |

buy fixed assets is probably a sign of credit status for these constrained firms. For other variables, the estimated coefficients are different for the two regressions. This reflects the presence of heterogeneity in the two subsamples, in line with the descriptive statistics (Table 4).

Foreign ownership contributes to high capacity utilization for constrained firms, but not for unconstrained firms. By contrast, overdraft financing reduces the level of capacity utilization for constrained firms but does not affect unconstrained firms. Constrained firms in the

TABLE 4 Mean and standard deviation of explanatory variables, by credit constraint status

| Variable | Constrained firm group | | Unconstrained firm group | | Difference |
|------------------------------|------------------------|-------|--------------------------|-------|------------|
| | Mean | SD | Mean | SD | |
| Capacity utilization | 68.14 | 22.01 | 72.46 | 19.59 | -4.318*** |
| Size: Medium | 0.338 | 0.473 | 0.366 | 0.482 | -0.028** |
| Size: Large | 0.118 | 0.323 | 0.290 | 0.454 | -0.172*** |
| Firm age | 2.995 | 0.813 | 3.083 | 0.797 | -0.088*** |
| Manager experience | 2.961 | 0.774 | 2.984 | 0.726 | -0.023 |
| Legal status | 0.865 | 0.342 | 0.923 | 0.266 | -0.059*** |
| Foreign ownership | 0.098 | 0.297 | 0.130 | 0.336 | -0.032*** |
| Part of larger establishment | 0.132 | 0.338 | 0.190 | 0.392 | -0.058*** |
| Informal credit sources: WC | 0.210 | 0.408 | 0.185 | 0.388 | 0.026** |
| Informal credit sources: FA | 0.461 | 0.499 | 0.285 | 0.452 | 0.176*** |
| Overdraft | 0.535 | 0.499 | 0.825 | 0.380 | -0.290*** |
| Sector: Food | 0.284 | 0.451 | 0.272 | 0.445 | 0.012 |
| Sector: Garments | 0.175 | 0.380 | 0.167 | 0.373 | 0.008 |
| Sector: Textiles | 0.087 | 0.282 | 0.085 | 0.280 | 0.001 |
| Sector: MLT | 0.221 | 0.415 | 0.225 | 0.417 | -0.004 |
| Sector: MHT | 0.137 | 0.344 | 0.161 | 0.368 | -0.024** |
| Productivity, lagged | 10.46 | 4.717 | 10.51 | 3.865 | -0.049 |
| Competitor: Second quantile | 0.169 | 0.375 | 0.225 | 0.417 | -0.055*** |
| Competitor: Third quantile | 0.162 | 0.368 | 0.230 | 0.421 | -0.068*** |
| Competitor: Fourth quantile | 0.180 | 0.384 | 0.217 | 0.412 | -0.037*** |
| Competitor: Many | 0.181 | 0.385 | 0.199 | 0.399 | -0.018 |

Abbreviations: MHT, medium-high-tech; MLT, medium-low-tech; SD, standard deviation.

*** and ** indicate significance at the 0.01 and 0.05 level, respectively.

second quantile for the number of competitors have lower capacity utilization than firms with fewer competitors (the base). For unconstrained firms, none of the quantile competition dummies are significant. We now turn to heterogeneity in capacity utilization in various manufacturing subsectors. For constrained firms, differences in the levels of capacity utilization of various subsectors are mainly explained by the explanatory variables in the model, as none of the subsector dummies is significant. For unconstrained firms, four out of the five subsector dummies are significant, indicating that other factors in the subsectors other than the explanatory variables in the model lead to various rates of capacity utilization for manufacturing subsectors.

5.3 | Counterfactual analysis

We further use Equations (8a)–(9b) to quantify the impact of credit status on capacity utilization for both the manufacturing subsectors and the entire sector. For

credit-constrained firms, the conditional expectation of observed capacity utilization is compared with the counterfactual expectation in the hypothetical case that they had not been constrained. Similarly, for unconstrained firms, the counterfactual expectation in the hypothetical case that they had not been constrained is compared with the conditional expectation of the realized capacity utilization. The defined difference is the “treatment effect” and it reflects the impact of credit constraints on the level of capacity utilization. A *T*-test is further used to test whether the mean difference is statistically significant. Table 6 presents the results.

As seen, the treatment effect is significant and negative in all cases. For constrained firms (the upper part of Table 6), lifting credit constraints would substantially raise capacity utilization. For unconstrained firms (the lower part of Table 6), capacity utilization would be lower if these firms had been credit constrained. The average treatment effect for all constrained firms is about -26.8%; this is about -23.7% for all unconstrained firms. Regarding subsectors and the constrained firm group, MLT and MHT firms have

TABLE 5 Estimation results of the endogenous switching model for capacity utilization

| Variable | Criteria equation (Credit-constraints) | | Capacity utilization | | | |
|------------------------------|---|-------|----------------------------|-------|------------------------------|-------|
| | | | (Credit-constrained firms) | | (Credit-unconstrained firms) | |
| | Estimate | SE | Estimate | SE | Estimate | SE |
| Intercept | 1.384*** | 0.150 | 73.90*** | 3.926 | 91.37*** | 4.048 |
| Size: Medium | -0.149*** | 0.045 | -1.903* | 1.155 | -1.373 | 1.010 |
| Size: Large | -0.416*** | 0.062 | -1.081 | 1.890 | -1.432 | 1.291 |
| Firm age | -0.035 | 0.026 | -0.540 | 0.666 | -0.791 | 0.566 |
| Manager experience | -0.058** | 0.027 | -1.483** | 0.694 | -0.867 | 0.583 |
| Legal status | -0.068 | 0.066 | -1.098 | 1.530 | 1.585 | 1.553 |
| Foreign ownership | 0.191*** | 0.064 | 1.496 | 1.786 | 1.511 | 1.314 |
| Part of larger establishment | -0.056 | 0.055 | 0.519 | 1.525 | 1.885* | 1.114 |
| Informal credit sources: WC | -0.028 | 0.066 | -5.890*** | 1.650 | -2.571* | 1.448 |
| Informal credit sources: FA | 0.259*** | 0.043 | -3.296*** | 1.176 | 1.598* | 0.986 |
| Overdraft | -0.805*** | 0.047 | -2.387 | 1.536 | -6.956*** | 1.350 |
| Sector: Food | 0.025 | 0.073 | 1.286 | 1.887 | 3.538** | 1.574 |
| Sector: Garments | -0.079 | 0.078 | 2.280 | 2.040 | 5.233*** | 1.705 |
| Sector: Textiles | -0.021 | 0.091 | -0.654 | 2.361 | 3.210* | 1.966 |
| Sector: MLT | 0.005 | 0.075 | -0.163 | 1.955 | 3.708** | 1.622 |
| Sector: MHT | -0.010 | 0.080 | -1.158 | 2.127 | 2.350 | 1.720 |
| Bolivia | -0.475*** | 0.079 | -10.96*** | 2.027 | -11.06*** | 1.793 |
| Ecuador | -0.239** | 0.094 | -3.679 | 2.390 | -0.343 | 2.061 |
| Paraguay | -0.470*** | 0.078 | -6.994*** | 2.019 | -6.787*** | 1.667 |
| Peru | -0.950*** | 0.057 | -7.366*** | 1.879 | -9.482*** | 1.235 |
| Uruguay | -0.352*** | 0.069 | -4.615*** | 1.695 | -5.627*** | 1.526 |
| Year: 2006 | 0.078 | 0.053 | 2.099 | 1.459 | 4.187*** | 1.164 |
| Year: 2010 | -0.083* | 0.051 | 1.363 | 1.745 | 0.632 | 1.177 |
| Audit | -0.198*** | 0.038 | | | | |
| Growth: Second quantile | -0.146*** | 0.048 | | | | |
| Growth: Third quantile | -0.244*** | 0.048 | | | | |
| Growth: Fourth quantile | -0.328*** | 0.049 | | | | |
| Productivity, lagged | | | 0.200* | 0.105 | 0.223** | 0.088 |
| Competitor: Second quantile | | | -4.995*** | 1.584 | 0.477 | 1.240 |
| Competitor: Third quantile | | | -0.661 | 1.589 | -0.334 | 1.269 |
| Competitor: Fourth quantile | | | -2.290 | 1.709 | -1.309 | 1.332 |
| Competitor: Many | | | 0.416 | 1.571 | -0.155 | 1.284 |
| Sigma | | | 22.44*** | | 23.67*** | |
| Rho | | | 0.395*** | | 0.846*** | |

Abbreviations: MHT, medium-high-tech; MLT, medium-low-tech.

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

higher treatment effects than food and other LT firms, but lower treatment effects than the textile and garments subsectors. For unconstrained firms, the counterfactual treatment effects for MLT and MHT firms are higher than the

effects for all LT subsectors, with the exception of the garments industry. Above all, the rates of capacity utilization of MHT and MLT firms are more severely affected by credit status compared with other LT firms.

TABLE 6 Average expected capacity utilization and treatment effects (%), by industry sector

| Credit-constrained firms | | | |
|-----------------------------------|---------------------------------------|---------------------------------------|--------------------------|
| Sector | Expectation of observed values | Counterfactual expectation | Treatment effects |
| Low-tech (LT): Other | 59.3 | 84.3 | -25.0*** |
| LT: Food | 62.5 | 88.4 | -25.9*** |
| LT: Garments | 62.8 | 90.6 | -27.7*** |
| LT: Textiles | 60.9 | 89.1 | -28.2*** |
| Medium-low-tech (MLT) | 59.8 | 86.1 | -26.3*** |
| Medium-high-tech (MHT) | 61.4 | 89.0 | -27.6*** |
| Whole sample | 61.5 | 88.3 | -26.8*** |
| Credit-unconstrained firms | | | |
| Sector | Counterfactual expectation | Expectation of observed values | Treatment effects |
| LT: Other | 58.2 | 79.5 | -21.4*** |
| LT: Food | 60.5 | 83.4 | -22.9*** |
| LT: Garments | 61.0 | 84.5 | -23.5*** |
| LT: Textiles | 58.3 | 83.2 | -24.9*** |
| MLT | 56.7 | 80.8 | -24.0*** |
| MHT | 58.4 | 83.7 | -25.2*** |
| Whole sample | 59.1 | 82.9 | -23.7*** |

***indicates significance at the 0.01 level.

6 | ROBUSTNESS AND ADDITIONAL TESTS

6.1 | Alternative estimation methods

In the study, the share of a firm's actual output out of its maximal output measures its capacity utilization, indicating the values of capacity utilization in the range between zero and one. Like other rates, the distribution of capacity utilization is asymmetric and right-skewed, for which the endogenous switching model does not account. As a robustness check, we applied the beta regression approach proposed by Ferrari and Cribari-Neto (2004) to estimate the models. The beta regression approach assumes that the dependent variable (ratio or proportion) is beta-distributed, which easily accommodates asymmetries (Cribari-Neto & Zeileis, 2010). Since some firms have full capacity utilization, the right-closed unit interval is transformed into the open unit interval for implementing the beta regression. For controlling for endogeneity, we first estimated the probit model for *Credit-Constraints*. The fitted value from the probit model is incorporated into the capacity utilization model. We further modified the basic specification by adding interaction terms between capacity utilization and dummies for manufacturing subsectors to test whether the link between credit constraints and capacity utilization varies across these subsectors. Table 7 presents the estimation results.

In Table 7, the values under criteria equation are estimation results for the probit model for *Credit-Constraints*. None of the dummies for manufacturing subsectors are significant, indicating the lack of correlation between the probability of being credit constrained and firms' technological level, the same results as the ones from the endogenous switching model. The beta regression using the full sample indicates that a negative and significant impact of *Credit-Constraints* on the rate of capacity utilization, in line with the negative treatment effect for all sample firms generated from the counterfactual analysis in section 5.3. The beta regression results for the full sample and with interaction terms between the fitted *Credit-Constraints* and manufacturing subsectors indicate that the individual dummies for subsectors are not significant and that all the interaction terms, except for the one with MHT, are significant and positive. The empirical findings from the beta regression approach verify the robustness of the estimation results for the constrained and unconstrained firm groups using the endogenous switching model.

6.2 | Credit constraints and capital productivity

We further examined the impact of credit constraints on capital productivity and labor productivity. This further provides explanations for the different impacts of

TABLE 7 Estimation results of beta regression for capacity utilization

| Variable | Criteria equation (Credit-constraints) | | Capacity utilization | | | |
|-------------------------------|---|-------|----------------------|----------|------------------------------|-------|
| | Estimate | SE | Full sample | | Full sample with interaction | |
| | | | Estimate | SE | Estimate | SE |
| Intercept | 0.910*** | 0.186 | 2.541*** | 3.926 | 2.779*** | 0.408 |
| Size: Medium | -0.220*** | 0.054 | -0.186*** | 1.155 | -0.185*** | 0.058 |
| Size: Large | -0.566*** | 0.077 | -0.338*** | 1.890 | -0.338*** | 0.107 |
| Firm age | 0.017 | 0.033 | -0.046* | 0.666 | -0.047* | 0.026 |
| Manager experience | 0.017 | 0.033 | -0.022 | 0.694 | -0.021 | 0.027 |
| Legal status | -0.118 | 0.081 | -0.038 | 1.530 | -0.044 | 0.07 |
| Foreign ownership | 0.292*** | 0.078 | 0.174** | 1.786 | 0.167** | 0.072 |
| Part of larger establishment | -0.033 | 0.066 | -0.04 | 1.525 | -0.034 | 0.052 |
| Informal credit sources: WC | 0.058 | 0.078 | -0.188*** | 1.650 | -0.184*** | 0.063 |
| Informal credit sources: FA | 0.233*** | 0.052 | -0.034 | 1.176 | -0.038 | 0.057 |
| Overdraft | -0.934*** | 0.054 | -0.451*** | 1.536 | -0.451*** | 0.168 |
| Sector: Food | -0.050 | 0.087 | 0.19*** | 1.887 | -0.057 | 0.147 |
| Sector: Garments | -0.129 | 0.092 | 0.222*** | 2.040 | -0.065 | 0.157 |
| Sector: Textiles | -0.078 | 0.109 | 0.189** | 2.361 | -0.075 | 0.18 |
| Sector: MLT | 0.0001 | 0.088 | 0.283*** | 1.955 | -0.084 | 0.152 |
| Sector: MHT | 0.015 | 0.096 | 0.119 | 2.127 | 0.02 | 0.158 |
| Bolivia | -0.410*** | 0.094 | -0.623*** | 2.027 | -0.617*** | 0.097 |
| Ecuador | -0.185* | 0.111 | -0.044 | 2.390 | -0.037 | 0.09 |
| Paraguay | -0.227** | 0.098 | -0.156** | 2.019 | -0.159** | 0.078 |
| Peru | -0.906*** | 0.070 | -0.578*** | 1.879 | -0.576*** | 0.133 |
| Uruguay | -0.234*** | 0.086 | -0.202*** | 1.695 | -0.194*** | 0.074 |
| Year: 2006 | 0.133** | 0.067 | 0.186*** | 1.459 | 0.186*** | 0.058 |
| Year: 2010 | 0.003 | 0.064 | -0.027 | 1.745 | -0.029 | 0.06 |
| Audit | -0.140** | 0.055 | | | | |
| Growth: Second quantile | -0.041 | 0.067 | | | | |
| Growth: Third quantile | -0.151** | 0.067 | | | | |
| Growth: Fourth quantile | -0.133** | 0.068 | | | | |
| Productivity, lagged | | | 0.005 | 0.005 | -0.112* | 0.088 |
| Competitor: Second quantile | | | -0.118** | 0.058** | 0.025 | 1.240 |
| Competitor: Third quantile | | | -0.09 | 0.062 | -0.334 | 1.269 |
| Competitor: Fourth quantile | | | -0.117* | 0.065* | -1.309 | 1.332 |
| Competitor: Many | | | 0.014 | 0.063 | -0.155 | 1.284 |
| Credit-constraints | | | -1.942*** | 0.489*** | -2.502*** | 0.544 |
| Credit-constraints * Food | | | | | 0.59** | 0.313 |
| Credit-constraints * Garments | | | | | 0.688** | 0.332 |
| Credit-constraints * Textiles | | | | | 0.635* | 0.39 |
| Credit-constraints * MLT | | | | | 0.898*** | 0.324 |
| Credit-constraints * MHT | | | | | 0.188 | 0.344 |

Abbreviations: MHT, medium-high-tech; MLT, medium-low-tech; SD, standard deviation.

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

TABLE 8 Estimation results of the endogenous switching model for capital productivity

| Variable | Criteria equation | | Capital productivity | | | |
|------------------------------|----------------------|-------|----------------------------|-------|------------------------------|-------|
| | (Credit-constraints) | | (Credit-constrained firms) | | (Credit-unconstrained firms) | |
| | Estimate | SE | Estimate | SE | Estimate | SE |
| Intercept | 0.973*** | 0.183 | -0.181 | 0.340 | 1.040*** | 0.334 |
| Size: Medium | -0.216*** | 0.053 | 0.020 | 0.099 | 0.125 | 0.078 |
| Size: Large | -0.565*** | 0.076 | -0.338** | 0.159 | -0.168* | 0.100 |
| Firm age | 0.010 | 0.032 | -0.053 | 0.059 | -0.041 | 0.044 |
| Manager experience | 0.015 | 0.033 | 0.001 | 0.061 | -0.105** | 0.045 |
| Legal status | -0.086 | 0.080 | 0.487*** | 0.135 | 0.264** | 0.126 |
| Foreign ownership | 0.308*** | 0.077 | 0.580*** | 0.149 | 0.001 | 0.101 |
| Part of larger establishment | -0.019 | 0.066 | 0.143 | 0.127 | 0.135 | 0.084 |
| Informal credit sources: WC | 0.034 | 0.078 | -0.006 | 0.139 | 0.219* | 0.113 |
| Informal credit sources: FA | 0.209*** | 0.052 | 0.071 | 0.098 | 0.042 | 0.078 |
| Overdraft | -0.903*** | 0.054 | -0.674*** | 0.118 | 0.009 | 0.111 |
| Sector: Food | -0.052 | 0.086 | -0.165 | 0.158 | 0.050 | 0.120 |
| Sector: Garments | -0.126 | 0.092 | 0.225 | 0.168 | 0.279** | 0.128 |
| Sector: Textiles | -0.076 | 0.108 | -0.393** | 0.199 | -0.324** | 0.149 |
| Sector: MLT | -0.007 | 0.088 | 0.150 | 0.161 | 0.341*** | 0.123 |
| Sector: MHT | 0.007 | 0.095 | -0.207 | 0.176 | -0.175 | 0.131 |
| Bolivia | -0.396*** | 0.092 | -0.293* | 0.166 | -0.314** | 0.137 |
| Ecuador | -0.196* | 0.109 | -0.173 | 0.195 | -0.270* | 0.155 |
| Paraguay | -0.232** | 0.096 | -0.406** | 0.168 | -0.792*** | 0.133 |
| Peru | -0.900*** | 0.068 | -0.669*** | 0.143 | -0.074 | 0.097 |
| Uruguay | -0.227*** | 0.086 | 0.193 | 0.148 | 0.040 | 0.126 |
| Year: 2006 | 0.128* | 0.066 | 0.270** | 0.127 | 0.200** | 0.091 |
| Year: 2010 | -0.004 | 0.063 | 0.502*** | 0.151 | 0.596*** | 0.096 |
| Audit | -0.161*** | 0.049 | | | | |
| Growth: Second quantile | -0.125** | 0.061 | | | | |
| Growth: Third quantile | -0.249*** | 0.060 | | | | |
| Growth: Fourth quantile | -0.238*** | 0.062 | | | | |
| Productivity, lagged | | | 0.024*** | 0.009 | 0.022** | 0.009 |
| Competitor: Second quantile | | | -0.386*** | 0.130 | 0.104 | 0.111 |
| Competitor: Third quantile | | | 0.053 | 0.122 | 0.197* | 0.117 |
| Competitor: Fourth quantile | | | 0.131 | 0.133 | 0.151 | 0.120 |
| Competitor: Many | | | 0.017 | 0.129 | 0.062 | 0.117 |
| Sigma | | | 1.730*** | | 1.440*** | |
| Rho | | | 0.724*** | | 0.250*** | |

Abbreviations: MHT, medium-high-tech; MLT, medium-low-tech; SD, standard deviation.

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

credit constraints on capacity utilization for various manufacturing subsectors.

Capital productivity is defined as the ratio of sales to fixed assets. Due to data availability, sales rather than

production are used as a proxy of output. In addition, fixed assets are measured as the replacement value of the assets in the current condition, following Gorodnichenko and Schnitzer (2013). Both input and output in the measurement

TABLE 9 Estimation results of the endogenous switching model for labor productivity

| Variable | Criteria equation | | Labor productivity | | | |
|------------------------------|----------------------|-------|----------------------------|-------|------------------------------|-------|
| | (Credit-constraints) | | (Credit-constrained firms) | | (Credit-unconstrained firms) | |
| | Estimate | SE | Estimate | SE | Estimate | SE |
| Intercept | 1.562*** | 0.152 | 9.639*** | 0.187 | 10.17*** | 0.177 |
| Size: Medium | -0.139*** | 0.046 | 0.119*** | 0.055 | 0.182*** | 0.044 |
| Size: Large | -0.439*** | 0.063 | 0.168 | 0.086 | 0.300** | 0.055 |
| Firm age | -0.038*** | 0.027 | 0.043 | 0.032 | 0.032 | 0.025 |
| Manager experience | -0.058*** | 0.028 | -0.014 | 0.033 | -0.002 | 0.025 |
| Legal status | -0.023*** | 0.067 | 0.378 | 0.075 | 0.485*** | 0.069 |
| Foreign ownership | 0.213*** | 0.066 | 0.739** | 0.085 | 0.505*** | 0.056 |
| Part of larger establishment | -0.079 | 0.056 | 0.138** | 0.073 | 0.149*** | 0.048 |
| Informal credit sources: WC | -0.034** | 0.067 | -0.013 | 0.080 | -0.107 | 0.063 |
| Informal credit sources: FA | 0.266 | 0.043 | 0.016 | 0.055 | 0.028 | 0.043 |
| Overdraft | -0.857*** | 0.047 | -0.213*** | 0.060 | 0.020*** | 0.057 |
| Sector: Food | 0.037 | 0.074 | -0.091*** | 0.091 | 0.243*** | 0.068 |
| Sector: Garments | -0.083 | 0.081 | -0.321* | 0.098 | -0.404*** | 0.074 |
| Sector: Textiles | -0.047*** | 0.094 | -0.148 | 0.114 | -0.219* | 0.085 |
| Sector: MLT | 0.037*** | 0.077 | 0.264 | 0.094 | 0.278 | 0.070 |
| Sector: MHT | -0.011 | 0.082 | 0.114*** | 0.102 | 0.078 | 0.074 |
| Bolivia | -0.478 | 0.081 | -1.310 | 0.095 | -1.120*** | 0.078 |
| Ecuador | -0.281 | 0.096 | -0.459*** | 0.114 | -0.365*** | 0.090 |
| Paraguay | -0.458 | 0.079 | -1.158 | 0.096 | -0.919** | |
| Peru | -1.092 | 0.057 | -1.014*** | 0.078 | -0.604*** | 0.052 |
| Uruguay | -0.422*** | 0.070 | -0.434 | 0.081 | -0.176 | 0.067 |
| Year: 2006 | 0.068*** | 0.054 | -0.347*** | 0.069 | -0.237*** | 0.051 |
| Year: 2010 | -0.126*** | 0.052 | -0.169*** | 0.081 | -0.136*** | 0.052 |
| Audit | -0.344*** | 0.040 | | | | |
| Growth: Second quantile | -0.184*** | 0.050 | | | | |
| Growth: Third quantile | -0.305 | 0.050 | | | | |
| Growth: Fourth quantile | -0.420** | 0.050 | | | | |
| Productivity, lagged | | | 0.018*** | 0.005 | 0.036*** | 0.004 |
| Competitor: Second quantile | | | -0.054 | 0.072 | 0.124** | 0.060 |
| Competitor: Third quantile | | | -0.014 | 0.071 | 0.026 | 0.062 |
| Competitor: Fourth quantile | | | -0.009 | 0.076 | 0.075 | 0.064 |
| Competitor: Many | | | -0.014 | 0.070 | 0.231*** | 0.062 |
| Sigma | | | 1.153*** | | 0.973*** | |
| Rho | | | 0.715*** | | 0.599*** | |

Abbreviations: MHT, medium-high-tech; MLT, medium-low-tech; SD, standard deviation.

***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

of capital productivity are directly affected by credit availability despite the measure differing from standard methods. Credit-constrained firms are less likely to use trade credit to promote sales. Limited financial resources further prevent

firms from upgrading their existing facilities to enhance productivity (Almeida et al., 2004; Bellone et al., 2010), indicating lower replacement values of fixed assets owned by firms and hence lower capital utilization.

Due to missing observations for the replacement values of fixed assets, we use a restrictive subsample (3,524 observations) to estimate the model. The endogenous switching model is used for credit constraints and capital productivity. The independent variables are the same as in the capacity utilization model, and capital productivity is expressed in the logarithmic form. As shown in Table 8, the significant correlation coefficients between the error terms of the regression equations confirm the endogenous switching pattern of the model. According to the results of the regression equation for *Credit-Constraints*, all the sector dummies are insignificant. This is in line with findings in the capacity utilization model. The textiles sector has lower capital productivity than other LT firms (the base), regardless of whether firms are credit constrained or not. For other sector dummies, only the coefficients of the dummies for the garments industry and MLT firms are positive and significant. It is worth noting that large firms have lower capital productivity than small firms in both the constrained and unconstrained firm groups. However, the capacity utilization model shows no difference in capacity utilization levels for large and small firms.

6.3 | Credit constraints and labor productivity

In the production function represented by Equation (2), h is an index of capital utilization. Alternatively, h reflects the portion of total employees directly involved in production rather than in maintenance activities (Greenwood et al., 1988). In the literature, sales per employee measure labor productivity (Ballot, Fakhfakh, Galia, & Salter, 2015; Chen & Guariglia, 2013; Guisado-González, Vila-Alonso, & Guisado-Tato, 2016; Wagner, 2014). The input is the number of permanent and full-time employees.

Table 9 reports the estimation results for labor productivity, using the whole sample. The results first confirm the endogenous switching pattern since the two correlation coefficients are significant, in line with findings in the capacity utilization and capital productivity models. The dummy variables for the two earlier surveys are significant and negative in the two outcome regressions, indicating an upward trend of capacity utilization regardless of firms' financial status. In the constrained firm group, the food and garments industries have lower labor productivity than other LT firms, *ceteris paribus*; however, MHT firms have the highest labor productivity among all the subsectors. In the unconstrained firm group, MHT firms have the same productivity as other LT firms. All LT subsector dummies are significant with

either a positive or a negative sign, indicating heterogeneous labor productivity in the LT firm group. Unlike the estimations for labor productivity, medium-sized firms are more capital productive than small firms, for both constrained and unconstrained firms. Moreover, large unconstrained firms have the highest capital productivity. Since capacity utilization depends on both capital productivity and labor productivity, the opposite estimation results for firm size dummies from the capital productivity model and the labor productivity model may explain why the corresponding coefficients in the capacity utilization model are not significant.

Finally, we explore and compare the treatment effects of credit constraint conditions on capacity utilization, capital productivity, and labor productivity, although results from the capital productivity model (with a restricted sample) are less comparable to results from the capacity utilization and capital productivity models (with the full sample). Figure 1 illustrates the treatment effects by the manufacturing subsector (with the other LT firms as the base). As seen, MLT and MHT firms have higher treatment effects on capacity utilization than other LT firms. This may be due to labor productivity rather than capital productivity since for these firms, the treatment effects on labor productivity are much higher than the effects on capital productivity. The comparison results for LT firms are more divergent. Like MLT and MHT firms, garments firms have higher treatment effects on labor productivity but lower treatment effects on capital productivity, relative to other LT firms. Contrary to the

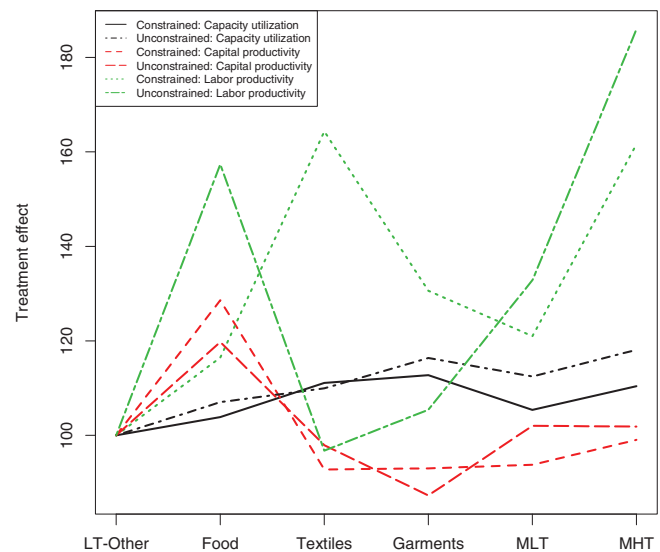


FIGURE 1 Treatment effects of credit constraints on capability utilization, capital productivity, and labor productivity, by manufacturing subsector. LT-Other = 100. See Table 1 for the list of manufacturing subsectors. LT, low-tech [Colour figure can be viewed at wileyonlinelibrary.com]

garments industry, the food industry has high treatment effects on both capital and labor productivities. This, however, does not raise treatment effects on capacity utilization to a sufficiently high level. In general, the direction of treatment effects is the same for constrained and unconstrained firms. The only exception is labor productivity for the textiles industry where constrained firms have higher treatment effects than unconstrained firms. The direction of treatment effects is the same for other cases, although the size of treatment effects is different for constrained and unconstrained firms, indicating heterogeneity in the two subsamples.

7 | CONCLUSION

This article uses firm-level data in six Latin-American countries to test the impact of credit constraints on capacity utilization for private manufacturing firms and investigate whether the link between credit constraints and capacity utilization varies across manufacturing subsectors. Capacity utilization affects macroeconomic indicators such as income distribution, inflation rate, productivity movement, and aggregate spending decisions (Nikiforos & Foley, 2012; Schoder, 2014). On the firm level, highly efficient utilization of capital and low spare capacity raise depreciation rates and stimulate the updating of current facilities (Greenwood et al., 1988). This is particularly important for developing countries where the manufacturing-led development strategies they have been pursuing depend largely on the updating processes in this sector. However, capacity utilization is relatively low in developing countries. The average capacity utilization for our sample firms is 70.7%, with a standard deviation of 20.7%. Among the determinants of capacity utilization, financial friction limits a firm's ability to choose optimal capacity utilization (Ahn & McQuoid, 2017). This is reflected in the sample firms. For both the sample as a whole and the manufacturing subsectors, credit-constrained firms have a lower rate of capacity utilization than credit-unconstrained firms. This raises the empirical issue of how to control for both endogeneity and heterogeneity to examine the impact of credit constraints on capacity utilization.

We applied an endogenous switching model to simultaneously estimate the equation for credit constraints and the equations for capacity utilization conditional on credit constraint conditions. The estimated correlation coefficients are statistically significant, indicating the existence of unobservable factors influencing both credit constraint conditions and capacity utilization. The probability of being constrained by credit access does not differ across manufacturing subsectors,

holding other factors constant. For constrained firms, capacity utilization is not affected by technological regimes. However, for unconstrained firms, dominant LT industries (food, garments, and textiles) and MLT firms more fully use their capacity than other LT firms. Counterfactual analysis is further applied to derive the counterfactual expectation of capacity utilization for constrained firms if they had been unconstrained and for unconstrained firms if they had been constrained. For constrained firms, the treatment effect (being constrained) is -26.8% for the whole sample and ranges between -28.2% and -25.0% for subsectors. For unconstrained firms, the treatment effect (being hypothetically constrained compared with unconstrained) is -23.7% for the whole sample and ranges between -25.2% and -21.4% for subsectors.

The negative impact of *Credit-Constraints* on capacity utilization may attribute to lower capital productivity or lower labor productivity. The estimation results of the endogenous switching model for capital productivity and labor productivity indicate that the negative treatment effects on capital productivity for MLT and MHT firms are slightly lower or close to the treatment effect for other LT firms; however, high technology firms' labor productivity responds more negatively to a credit constraint condition than other LT firms. In general, the depressed output is better explained by labor productivity than by capital utilization. This is particularly true for MLT and MHT firms, as indicated by the comparison results. Lower labor productivity is probably due to maintenance activities, downtime, or the low level of labor force skills, which generally respond directly and instantly to financial friction than physical capital. In the long run, credit constraints may affect capital productivity more severely for MLT and MHT firms, which rely more on capital input than LT firms.

This study provides evidence of the negative effects of credit constraints on capacity utilization for manufacturing firms. Lower capacity utilization is attributable to both capital productivity and labor productivity. Financial friction prevents firms from effectively optimizing capital and labor, updating new products, adopting new technologies, and improving labor skills. Unlike other determinants such as market uncertainty, credit constraints are almost beyond firm control yet can be alleviated with government supports. Exogenously lifting credit constraints stimulates updating processes in the manufacturing sector and increases capacity utilization rates. The results of the counterfactual analysis (regarding changes in capacity utilization for constrained firms had they not been constrained) provide support for predicting the outcomes of the financial support programs for manufacturing as a whole and subsectors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in World Bank Enterprise Surveys at <http://www.enterprisesurveys.org>.

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