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Productivity determinants in the construction sector in emerging country: New evidence from Ecuadorian firms

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Abstract

The construction sector is one of the most important sectors for economic development due, among other reasons, to the productive chains that it generates. This paper presents an analysis of the determinants of the total factor productivity (TFP) in the Ecuadorian construction sector during the period 2007–2018. In the first stage, we estimate a production function using the Wooldridge (*Economics Letters,* 2009, *104*, 112–114) estimator to correct the simultaneous determination of inputs and firm unobserved productivity. In the second stage, we analyze the main determinants of TFP. These determinants are classified into four groups: internal, international trade, financial constraints, and external characteristics. Our results suggest that firm age is positively related with TFP but negatively related with TFP growth. Similarly, the fact of being a family firm is negatively related with TFP, but size is positively related with TFP and its growth across the construction subsectors. In addition, we find that access to debt and credit is positively related with productivity, but less-competitive environment is negatively related with productivity. Finally, our results suggest that TFP and its growth are pro-cyclical with respect to the gross domestic product. Our results have several managerial implications that are discussed in this article.

KEYWORDS

construction, production, total factor productivity

JEL CLASSIFICATION

D24; L74; L78; L50

1 | INTRODUCTION

The relationships between the construction sector and economic growth are a topic that has been widely addressed by academia. Many authors have found positive (but sometimes marginal) associations between the construction industry development and country-level growth in developing economies (Anaman & Osei-Amponsah, 2007; Chan, 2002). The construction sector has been found to have a multiplier effect through the backward and forward relationships with other economics sectors (Park, 1989). This multiplier effect is also supported by the Keynesian tradition in which investment is an important pillar for sustaining demand (Wigren & Wilhelmsson, 2007).

Moreover, the dynamism of this sector is tightly bound to the business cycle of a country. Some empirical studies have found a positive correlation between changes in the role that the construction sector plays in a country and changes on its business cycle (Ruddock & Lopes, 2006; Tan, 2002). For instance, when a country is in its initial stages of economic development, the construction sector displays larger growth rates than other sectors. Nevertheless, as the country approaches its desired level of development, the growth of the construction industry, as well as the cycle of the gross domestic product (GDP), slows down. This relation between the business cycle and the growth of the construction sector takes the form of an inverted U (Bon, 1992; Sousa-Cruz et al., 2018).

Even though construction industry productivity levels can provide information on the sector development, firm-level productivity indicators are needed to understand distributional patterns of productivity within the sector. In other words, productivity growth at firm level is an important factor for determining an increase in productivity at the sectoral level; however, it is not the only one. For example, even if the firms within the sector do not experience any positive productivity growth, the sector could display a positive industry productive growth if employees relocate from firms with lower levels of productivity to firms with productivity levels above the average (Foster et al., 2008; Syverson, 2011).

We focus on seeking the determinants of firm-level productivity in the construction industry in a developing country setting. Contrary to other studies that have been focusing mainly on internal firm characteristics (e.g., managerial performance, labor productivity, capital stock management, technology, type of ownership),[1] our aim is to focus on some business environment characteristics that are important in determining productivity at firm level.

In Ecuador, the construction sector represented on average 8.9% of the GDP during the period 2007–2018. This sector is the fourth largest in the economy after the oil, manufacturing, and retail sectors. However, although this sector experienced positive growth rates during the period 2007–2014, 2011 being the year with the highest annual growth rate (+17.6%), it also experienced low and negative growth rates over the past 4 years. In 2016, it presented the lowest growth rate with a decline of 5.8% on the sector growth rate (Banco Central del Ecuador [BCE], 2020). The construction sector in Ecuador is characterized as being a competitive sector. It also has a large number of firms with family ownership; approximately 94% are family-owned firms.[2] In addition, 5% of the firms in the construction sector are large enterprises. Moreover, the construction industry has limited access to credit compared to other developing countries in the region[3]; approximately only 25% of the firms hold obligations to a financial institution.

In this sense, our aim in this paper is to provide a twofold contribution. First, unlike most previous evidence for the construction sector, we compute estimates of the total factor productivity (TFP) at firm level using semiparametric approaches that have been proven to provide more accurate productivity estimators given that they cope with simultaneity and endogenity issues (Van Beveren, 2012; Van Biesebroeck, 2007), especially when prices of inputs and outputs are available. The majority of the empirical evidence in terms of firm-level productivity levels in the construction sector has been relying on nonparametric measures that, given the flexibility introduced by this approach, are very sensible to outliers and are mostly used when input and output prices are unavailable (see, e.g., Azman et al., 2019; Chancellor & Lu, 2016; Horta et al., 2013; Li & Liu, 2010; Wang et al., 2013; Xue et al., 2008).

Second, we discuss important productivity drivers in the construction sector in a developing economy setting, broadening the scope of drivers to different clusters of characteristics that can be relevant for determining productivity at firm level: internal firm characteristics (i.e., age, family ownership, size, Return on Assets [ROA]), international trade activities (i.e., exports and imports), financial constraints (i.e., credit access and debt-to-equity indicators), and external characteristics (i.e., GDP cycle, industry concentration). Previous research has mainly focused on enlisting determinants of productivity at the industry level by analyzing the views of the industry's practitioners (Arditi & Mochtar, 2000). However, to improve cross-country comparisons and obtain more accurate conclusions about the productivity levels in a sector, characteristics that drive productivity at firm level must be investigated (Abdel-Wahab & Vogl, 2011), and this is possible through the available firm-level data from individual financial accounts that we try to exploit in our analysis. In this sense, we propose to analyze also (1) internal trade activities, which are consistent with the self-selection and the learning-by-exporting or importing hypothesis; (2) financial constraints, which are an important set of characteristics affecting especially small- and medium-sized firms; and (3) external characteristics related to macroeconomic and industry conditions.

We perform the analysis using an unbalanced panel data of firms from the construction sector in a developing economy setting, which has been scarcely explored. Moreover, we contrast different subsectors within the construction industry to obtain robust evidence of heterogeneity behavior in the use of inputs and therefore differences in productivity levels. We expect our contribution can be considered as a support for public policy makers and as a tool to improve the decision-making process made by entrepreneurs.

Our paper proceeds as follows. Section 2 presents a review of the literature on the importance of productivity related to the construction sector. Section 3 describes the methodology used to estimate the traditional production function, as well as the approach employed to obtain the main determinants of companies' productivity in the sector. Finally, Section 4 presents the results, and Section 5 discusses the implications of our findings and provides recommendations for future studies.

2 | LITERATURE REVIEW

The seminal literature on economic growth has been the main foundation of studies that estimate and analyze sectoral- and firm-level productivity through micro-data (Abramovitz, 1956; Solow, 1957). The availability of micro-data makes it possible to obtain productivity measures that control for the heterogeneity present across firms and analyze how firms react to different internal and external factors. Compared to aggregate productivity indicators, firm-level productivity measures provide more information about the performance of a certain sector given that firms are the cause of the economic activity. In this sense, it is important to understand how effectively firms allocate resources to generate such economic activity (Azman et al., 2019).

As widely known, productivity is the capacity that a firm has to efficiently produce a certain amount of goods and/or services (Syverson, 2011); that is, it indicates how efficient the firm can be when using a certain number of inputs in the production process. In this sense, firm productivity can be measured by individual indicators of productivity inputs (capital productivity, labor productivity, etc.), which reflect the impact of a given factor on production, or through the combination of different inputs in the final production, known as multifactorial productivity indexes (Crawford & Vogl, 2006). The TFP is a multifactorial index that is preferred by many economists because it includes a deeper analysis of those factors that contribute to sectorial growth, such as management strategies, technological progress, and unobservable as well as observable inputs (Crawford & Vogl, 2006; Gallop, 1985; Syverson, 2011).

However, there are inherent challenges regarding the measurement of productivity at the firm level. For instance, there are large and persistent heterogeneities in productivity estimations that have influenced many authors' research agendas (see Syverson, 2011, for a survey). In the past decades many authors have been interested in measuring the TFP at the firm level using more robust approaches (for more details, see Van Beveren, 2012; Van Biesebroeck, 2007).

Moreover, understanding how and to what extent different factors affect productivity is essential to improve public policies on different economic sectors. Although the variables that affect the TFP have been widely studied, these studies have been mainly focused on the analysis of the manufacturing, agro-industrial, and service sectors (see, e.g., Brandt et al., 2012; Fernandes, 2007; Harris & Moffat, 2015; Harris et al., 2005; Syverson, 2004), but there is scarce and inconclusive evidence for the construction industry, especially in emerging countries.

The majority of the initial analysis in the construction sector has estimated productivity through individual indicators of productivity inputs, especially through labor productivity (Chan, 2002; Chia et al., 2012; Yi & Chan, 2014). A few others have used nonparametric multifactorial productivity indexes, such as the Malquimist Index (Horta et al., 2013; Li & Liu, 2010; Wang et al., 2013; Xue et al., 2008), the Luenberger Index (Kapelko et al., 2015), and the F-P Index (Azman et al., 2019; Chancellor et al., 2015; Chancellor & Lu, 2016). These methods are popular especially when input and output prices are unavailable to estimate the parametric production function (O'Donnell, 2012). One main advantage of these types of indexes is that we need not assume a specific functional form that displays the behavior of the firms, so we allow the technology to vary freely across firms. However, Van Biesebroeck (2007) argues that the flexibility introduced by these estimators has certain disadvantages; the productivity estimators are, in this case, sensible to outliers, which raises a large concern when measurement errors exist in the data given that small shifts in a firm can affect all productivity estimates.

On the contrary, there is limited empirical evidence using parametric and semiparametric approaches in the construction industry (Harris, 2020; Zhi, Hua, Wang, & Ofori, 2003), as it has been widely used in other industries, especially in the manufacturing sector (Ding et al., 2016; Gonçalves & Martins, 2016; Harris & Moffat, 2015). The use of parametric and semiparametric methods to estimate the production function generates greater advantages because they allow us to capture the impact of the observed and unobserved inputs, and in addition, they allow us to research on possible characteristics that explain this index (Pearce, 2003).[4]

Apart from the different methodologies used in the TFP estimation, the majority of the studies that estimate productivity at firm level in the construction sector have been focused on analyzing mostly determinants from a point of view of internal characteristics but not from a broader economic point of view, including a different set of variables. Zhi et al. (2003) analyze the factors that influence the TFP growth for the construction sector in Singapore over the period 1984–1997 and find that variables such as production per person, proportion of foreign workers, levels of materials' quality, R&D expenditure, number of industrial accidents, and government regulations are related to the growth of TFP. Crawford and Vogl (2006) compare the TFP index with the average labor productivity in the United Kingdom and find a close relationship between these two measures. Also, they find that productivity growth has a cyclical behavior; for example, in the early stages of GDP growth, productivity increases markedly, but the opposite occurs when GDP decreases. On the contrary, Abdel-Wahab and Vogl (2011), who study TFP for several European countries, the United States, and Japan during the period 1990–2005, find that TFP is the largest contributor to economic growth and that the differences in labor productivity growth are highly associated with a poor performance of TFP.

In Latin America, there is little evidence of TFP analysis in the construction sector at firm level. Idrovo-Aguirre and Serey (2018) estimate the TFP in the construction industry at an aggregate level in Chile for the period 1986–2015 and find that the TFP shows a downward trend in the last 5 years of study. They also mention that the sector is highly influenced by the accumulation of factors and by the efficiency in the usage of inputs. Similarly, De Jorge Moreno et al. (2014) analyze productivity and its determining factors in four types of construction sectors in Colombia for the period 2005–2010, using a different technique, the data envelopment analysis, and find that only the productivity of the construction adequacy sector experiences a cumulative growth of 0.1% as a consequence of the improvement in efficiency in the presence of technological progress. They also find that company's size and market share are determinants of efficiency in the four sectors analyzed.

In general, most of the studies regarding productivity in developing countries have been done using sectorial estimators, and very few have been developed using firm-level data. Similarly, in Latin America the evidence about the factors that drive firm-level productivity is limited, and this subject needs further research. We combine different clusters of characteristics that are possible determinants of productivity in the construction sector in a developing country setting and try to understand how they drive productivity in the construction sector.

What characteristics can possibly affect the firm-level productivity in the construction sector?

Internal firm characteristics: Authors like Jovanovic (1982), Jovanovic and Nyarko (1996), and Pakes and Ericson (1998) argue that age is positively related with firm productivity because firms have a learning process; this hypothesis is the so-called learning-by-doing. However, new empirical evidence suggests that productivity decreases with age, supporting the vintage capital effect given that younger firms produce output with higher efficiency and with better technology than older plants (see, e.g., Harris & Moffat, 2015; Van Biesebroeck, 2005). Another important firm characteristic is having a "family" ownership (FF [family firm]); however, the relationship between being an FF and productivity is not clear. Bloom et al. (2010) argue that without delegating decision-making firms in developing countries, growth becomes unprofitable, or even impossible, because decisions are constrained by their owners' time; and this could negatively affect productivity (see, e.g., Barbera & Moores, 2013). Firm profitability could also be associated with its productivity; it would be expected that more profitable firms are more productive or vice versa. Finally, in this category we include firm size. It is well known that large firms have higher productivity than smaller firms because they have access to credit, international markets, innovative process, and better human resources; pay higher wages; and so on (see, e.g., Melitz & Ottaviano, 2008; Rochina-Barrachina et al., 2010; Van Biesebroeck, 2005).

International trade activities: A large amount of empirical literature argues that firms engaged in international trade activities via export and/or import have a positive effect on their productivity levels (for an extensive literature review, see Cassiman & Golovko, 2018; Wagner, 2012). In addition, the most analyzed mechanisms that support the hypothesis that exporter and/or importer firms outperform their counterparts are the self-selection and the learning-by-exporting or importing hypothesis. The idea behind this is that firms with high productivity levels tend to decide to export (but this could be the same to import inputs and/or capital goods), which suggests that only the most productive firms enter the international market (Wagner, 2007) and supports the self-selection effect. Also, the learning hypothesis argues that firms in the international markets can take advantage of economies of scale and acquire knowledge from greater exposure to better practices, which foster learning (Fariñas & Martín-Marcos, 2007).

Financial constraints: It is well known that credit access affects growth through the impact on productivity, because facilitating long-run, productivity-enhancing investment increases growth and reduces volatility (Aghion et al., 2010). However, one of the main problems for the firms to survive and to expand is the access to credit, in particular in developing countries. Moreover, this issue is mostly relevant in smaller firms than larger ones, which could affect aggregate productivity growth (see, e.g., Cao & Leung, 2020; Kochar, 1997; Van Biesebroeck, 2005). In this sense, we consider the ratio of debt-to-equity (*dte*) and credit access (*credit*) to analyze the relationship between financial constraints and productivity.

External characteristics: A higher level of competition could, for instance, increase productivity because firms could adopt new technologies, allocating products and services of higher quality in the market and operating more efficiently (see, e.g., Meyer & Vickers, 1997; Nickell, 1996). Behind the former idea, we include the Herfindahl–Hirschman Index (HHI) to capture the degree of competition that the sector holds. In addition, it is widely known that the construction sector is pro-cyclical with GDP (Crawford & Vogl, 2006). In this sense, we include the GDP cycle using the methodology proposed by Hodrick and Prescott (1997).

Most of the characteristics explained in this section have been scarcely addressed in the analysis of productivity at firm level, especially in developing economies and in particular in the construction sector. Using a rich set of micro-data with firms' accounting information, we investigate these characteristics as determinants of productivity from a broader economic perspective with semiparametric estimates that have been demonstrated to be more robust to endogeneity and autocorrelation issues in the choice of inputs.

3 | METHODOLOGY

In this section we describe the methodology used for the TFP estimation. Moreover, we discuss the approach employed to analyze the different types of determinants that could have affected the productivity for the Ecuadorian construction sector during the period 2007–2017. First, we describe the micro-level data used for the econometric analysis, both on the estimation of the production function and on the analysis of determinants of productivity. Then, we describe the identification strategies employed.

3.1 | Specification of the production function

In the construction industry, Zhi et al. (2003) used the model proposed by Jorgenson et al. (1987) to estimate the production function and then recover the TFP. This methodology is based on the seminal works of economic growth of Solow (1957), Denison (1967), and Romer (1986). The model consists of estimating TFP through a production function for each industry that is based on intermediate goods, capital and labor inputs, and time, which is expressed in the following equation:

$$Y = AF(K, L, M, T) \tag{1}$$

However, we adopt the traditional production function to be estimated at firm level i in industry j for year t, which is given by

$$Y_{ijt} = e^{(\omega_{ijt} + \varepsilon_{ijt})} K_{ijt}^{\beta} L_{ijt}^{\alpha} M_{ijt}^{\gamma} \tag{2}$$

where ω_{ijt} is a serially correlated productivity shock (not observed by the econometrician but observable or predictable by firms), K_{ijt} is the capital input, L_{ijt} is the labor input, M_{ijt} are the intermediate inputs, and ε_{ijt} is a standard i.i.d (Independent and identically distributed). error term that is neither observable nor predictable by the firm. The TFP is defined as $e^{(\omega_{ijt} + \varepsilon_{ijt})} = \frac{Y_{ijt}}{K_{ijt}^{\beta} L_{ijt}^{\alpha} M_{ijt}^{\gamma}}$. Then, from Equation 2 we get

$$\ln\left(e^{(\omega_{ijt} + \varepsilon_{ijt})}\right) = \ln A(\omega) = \omega_{ijt} + \varepsilon_{ijt} \tag{3}$$

Production function analysis allows for controlling the effects of observed plant-specific characteristics; in this sense, we control for a vector of dummy variables representing cities (Guayaquil, Quito, Cuenca, and others), year (2007–2018), and industry economic sectors at two digits of ISIC (International Standard Industrial Classification) rev 4 (z_{kijt}). Taking logarithms of Equation 2, we get the equation to be estimated as follows:

$$y_{ijt} = \omega_{ijt} + \beta k_{ijt} + \alpha l_{ijt} + \gamma m_{ijt} + \sum_{k} \psi_k z_{kijt} + \varepsilon_{ijt} \tag{4}$$

where the parameters β, α, and γ are elasticities of output with respect to each input. ε_{ijt} is the transmitted productivity, and it is the error component uncorrelated with input factors (ergo i.i.d.), respectively (Petrin et al., 2004). Equation 4 is used to estimate the production function for the overall Ecuadorian construction sector and the three subsectors obtained from the ISIC. Then, using the estimated elasticities for each production input, we calculated the TFP using the following equation:

$$\hat{\omega}_{ijt} = y_{jit} - \hat{\beta} k_{ijt} - \hat{\alpha} l_{ijt} - \hat{\gamma} m_{ijt} \tag{5}$$

However, recent literature on production function and TFP suggests that estimating Equation 4 by ordinary least squares (OLS) could generate biases on the estimated elasticities of the inputs, since it overestimates the coefficients (endogeneity of the inputs), particularly capital coefficients (endogeneity of waste) (Olley & Pakes, 1996), causing biases related to the heterogeneity in the inputs of technology that firms often employ to produce certain amount of outputs (De Loecker, 2007). Similar conclusions are obtained by estimating Equation 4 using fixed-effect (FE) estimators (first-difference and intra-group estimators) and random effects, which are also parametric methods used in the estimation of the production function. Nevertheless, the first includes a "fixed" idiosyncratic component assuming the invariability of the error through time, that is, ignoring the existence of serial correlation. This is a very risky assumption, since firm productivity is found in most sectors related to the economic cycle of a country; therefore, it is susceptible to macroeconomic shocks. Blundell and Bond (2000) relax this assumption and mention that productivity is broken down into two components: a fixed component and an autoregressive AR(1) component, supporting the existence of serial correlation. In addition, the FE model imposes strict exogeneity, conditioning inputs (particularly capital) to the heterogeneity of firms, even in the same sector (Van Beveren, 2012). Van Biesebroeck (2007) mentions that with many errors of measurement or with the technological differences existing between firms in the sector, the generalized method of moments (GMM)-System (SYS) estimator (Blundell & Bond, 1998) provides the most robust level of productivity of the growth estimates of traditional parametric methods.

Van Biesebroeck (2007), Van Beveren (2012), and Bournakis and Mallick (2018) review the parametric, semiparametric, and nonparametric methods for estimating production functions and explain their benefits and disadvantages. For example, Van Biesebroeck (2007) mentions that the Olley–Pakes (OP) estimator is the most reliable method when firms are subject to idiosyncratic productivity shocks that are not entirely transitory, because it will exploit the firm's knowledge about these shocks and if shocks are persistent. In addition, if the output is measured with error, this approach purges random noise from the productivity estimates, providing accurate results, especially for productivity levels. However, the prevalence of zero investment in a significant number of cases casts doubt on the validity of the monotonicity condition (Van Beveren, 2012).[5] In this vein, Levinsohn and Petrin (2003) propose an alternative estimator (Levinsohn and Petrin [LP]), which uses intermediate inputs as a proxy for unobserved productivity rather than investment. This change implies that the productivity is expressed as a function of capital and raw materials and does not incorporate the survival probability and correct for the selection bias. In addition, Van Beveren (2012) mentions that regarding the traditionally poor performance of both the GMM and FE estimators, it would seem that the semiparametric estimators are to be preferred. The main advantages of the LP estimator compared with the OP estimator are that the number of observations can be analyzed and that the researcher can retain the full sample of firms in the first stage.

Finally, Ackerberg et al. (2015) and Wooldridge (2009) correct the simultaneous determination of inputs and unobserved productivity by proxying the latter with firm-level intermediate inputs and FEs (Case lli, 2018). In this sense, we estimate Equation 4 by using the Wooldridge (2009) estimator (WDRG) with FEs similar to Case lli (2018), since this estimator does not assume constant returns to scale, is robust to the Ackerberg et al. (2015) criticism to the LP estimator, and is programmed as a simple instrumental variable estimator.

3.2 | TFP determinants in the construction industry

In this sense, once the TFP is estimated as in Equation 5, we proceed to assess which variables are significant determinants of TFP and its growth in a second-stage regression[6] as follows:

$$\widehat{\omega}_{ijt} = \alpha + \varphi_x X_{ijt} + \varepsilon_{ijt} \tag{6}$$

Moreover, to analyze the effect on future productivity and capture the determinants in TFP growth, we estimate the following equation:

$$\Delta\widehat{\omega}_{ijt} = \alpha + \varphi_x X_{ijt} + \varepsilon_{ijt} \tag{7}$$

where $\widehat{\omega}_{ijt}$ is the estimated TFP by the WDRG estimator, X_{ijt} is a vector of observed variables for the determination of the TFP and its growth, and ε_{ijt} is the error term. On what concerns the explanatory variables (X_{ijt}) we divide it analysis according to four different categories to analyze their effect TFP and its growth determinants.

3.3 | Data structure

We use a novel, underexplored, and administrative panel data with accounting information from financial statements reported annually to the Superintendencia de Compañías, Valores y Seguros

(SCVS)[7] by all the population of Ecuadorian construction formal firms during the period 2007–2018. We use an unbalanced panel data set, which includes information from 23,256 observations and 5,087 companies that reported financial statements during our period of analysis. These data provide information on firm-level characteristics and financial accounts that allow us to estimate the production function (all measured in real values, using the respective annual price deflater) and capture the TFP determinants. Furthermore, our analysis is based on all the firms that are operating for all the years in the sample period and without restrictions on the number of employees or business age; this allow us to use a large number of active firms in each year, city, and industry sector.

To estimate the production function, we use a filtering criterion similar to that of Camino-Mogro et al. (2018) that uses a similar database. We eliminate firms with inconsistent accounts: this is, firms with less than or equal to zero formal workers, gross revenue, net fixed assets, total intermediates, and wages. In addition, we analyze only active firms (according to the Ecuadorian legislation) in each year of our analysis.

Something important to mention is that our data set provides information only on sales in monetary units but not on quantities sold. In this sense, we estimate a revenue function. This implies that the estimated productivity is a revenue TFP and differences in prices and productivity effects cannot be detected (see, e.g., Caselli, 2018; De Loecker et al., 2016).

In Table 1 we describe each of the variables used in the TFP estimation for the construction sector, as well as the variables used in the analysis of factors that affect the business productivity of this sector. We also present the descriptive statistics of each variable analyzed in the production function and in the determinants of TFP. In particular, we show that the TFP mean growth across the years analyzed is 5.4%, the mean firm age is 6 years, 94.2% are FFs, the ROA is 0.078, only 5.2% are large firms and 94.8% are Micro, Small and Mediums, only 2.5% are exports, 0.9% are imports, the mean of debt-to-equity ratio is 1.334, and 24.8% of firms have some kind of credit (short- or long-run loan). Furthermore, we show that the HHI (in logs) is –3.617, meaning that the construction sector is not concentrated and is highly competitive; the mean GDP cycle is –0.001, suggesting that during 2007–2018 the Ecuadorian GDP cycle is below the growth trend.

This information reveals several characteristics of the construction sector in Ecuador; in particular, it shows that there are a large number of small companies, family-run businesses, which are located in the three most important cities in the country, little internationalized and relatively young companies. These characteristics are what Ruiz-Arranz et al. (2018) mention as the main determinants of having low business productivity in developing countries and specifically in the Andean region.

In addition, Figure 1a shows that on average the construction sector has a HHI of 3.2% during the period 2007–2018, which indicates that it is a nonconcentrated market and highly competitive industry according to the Department of Justice of the United States and the Federal Trade Commission (U.S. Department of Justice & FTC, 2010).[8] The CR4 index, which represents the participation of the four firms with the highest levels of revenue with respect to all participant firms in the construction industry, oscillates around 20% and 30% throughout the period of analysis, the year 2014 being the period that shows the highest levels of concentration in this sector. This also suggests that this sector is highly competitive and there is no suspicion of market power. Figure 1b shows the structure of the construction industry by disaggregating into different economic subsectors. The subsector that comprises the civil engineering works has the highest levels of concentration, according to the HHI index; nevertheless, it is a nonconcentrated market and highly competitive industry according to the Department of Justice of the United States and the Federal Trade Commission (U.S. Department of Justice & FTC, 2010); something similar occurs with the other subsectors.

Figure 2 shows the average TFP obtained for each year, as well as the growth rate of average productivity in logarithms by year. In addition, the TFP average for each subsector and the Kernel density

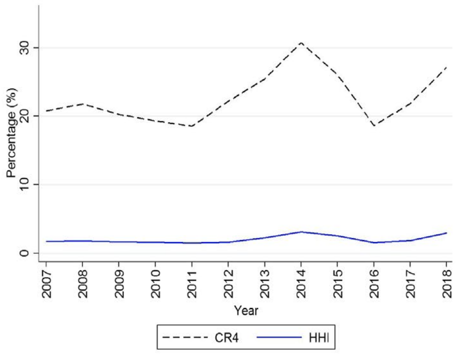
TABLE 1 Definition and descriptive statistics for variables used in TFP estimation and its determinants

Variable	Definition	Observations	Mean	*SD*
Y	ln (total revenues from sales). This variable is deflated using the industry-specific price index obtained from the Ecuadorian National Institute of Statistics.	23,256	12.461	1.959
L	ln (number of legally registered employees).	23,256	10.493	2.541
K	ln (net tangible assets). It is the sum of the real dollar value of buildings, machinery, and vehicles, assuming a depreciation of 5%, 10%, and 20%, respectively, similar to Bravo-Ortega et al. (2014). We measure the capital stock with the gross investment in equipment in year t (I_{it}), net fixed assets in real value (physical capital in year $t-1$) (k_{it-1}), a depreciation rate (d_{it}), and the price index for equipment at the industry level (P_t) obtained from the Ecuadorian National Institute of Statistics.	23,256	1.870	1.304
M	ln (intermediate inputs). This variable is deflated using the industry-specific price index obtained from the Ecuadorian National Institute of Statistics.	23,256	9.858	2.631
TFP	Natural logarithm of TFP.	23,256	7.712	1.311
TFP growth	First difference of TFP.	16,341	0.054	1.158
Age	ln (firm age). It is measured as the difference between the current year and the year the firm registered to start business in the country's mercantile register.	23,256	1.835	0.966
FF	Dummy variable is equal to 1 if the firm is a family firm at time *t*, 0 otherwise. We use the methodology proposed by Camino-Mogro and Bermudez-Barrezueta (2018).	22,590	0.942	0.232
ROA	ln ((profit/total assets) + 1)	23,256	0.078	0.123
Size[a]	Dummy that takes the value of 1 if the company is a large firm and 0 otherwise.	23,256	0.052	0.222
Exports	Dummy variable is equal to 1 if the firm exports at time *t*, 0 otherwise.	23,256	0.025	0.155
Imports	Dummy variable is equal to 1 if the firm imports intermediate inputs at time *t*, 0 otherwise.	23,256	0.009	0.094
dte	ln ((total liabilities/equity) + 1)	21,639	1.334	1.217
Credit	Dummy variable is equal to 1 if the firm receives a credit by any financial institution at time *t*, 0 otherwise.	23,256	0.248	0.431
HHI	ln (Herfindahl–Hirschman Index of industrial concentration [by two-digit ISIC])	23,256	–3.617	0.594
GDP cycle	GDP cycle using the Hodrick–Prescott filter of natural logarithm of real GDP.	23,256	–0.001	0.016
Large cities	Dummy that takes the value of 1 if the company belongs to Guayaquil, Quito, or Cuenca and 0 if it belongs to other cities.	23,256	0.707	0.455

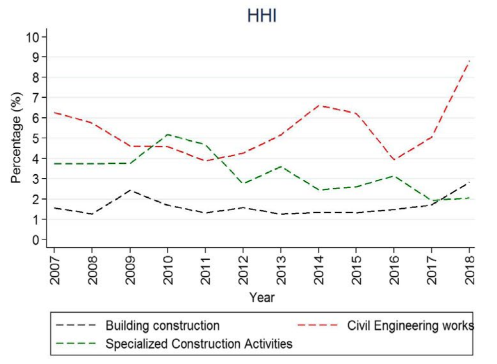
Abbreviations: dte = debt-to-equity; FF = family firm; GDP = gross domestic product; HHI = Herfindahl–Hirschman Index; ISIC = International Standard Industrial Classification; *SD* = standard deviation; TFP = total factor productivity.

Elaboration: Authors.

[a]The variable size has been determined according to the definition of the Organic Code of Production, Trade and Investment (2010).

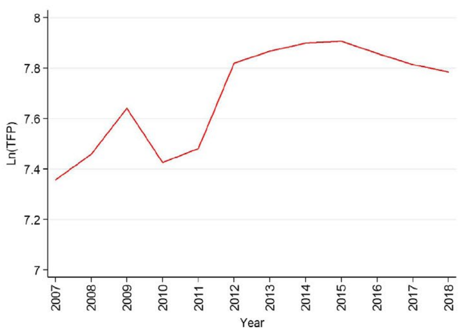


(a) CR4 and HHI measures

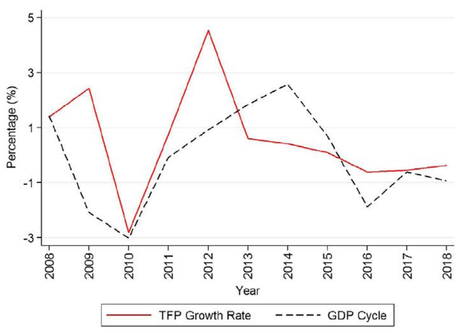


(b) HHI index by sub-sectors

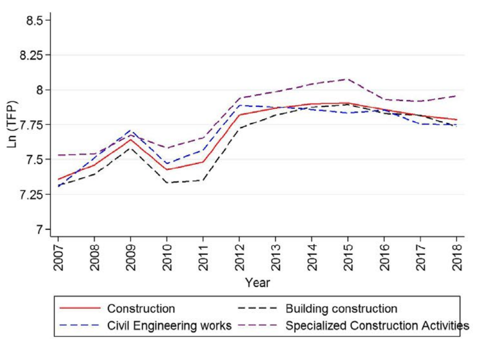
FIGURE 1 Concentration indexes in the construction sector (2007–2018). HHI = Herfindahl–Hirschman Index; CR4 = four-firm concentration ratio. We converted the HHI in the range from 0 to 1. (a) CR4 and HHI measures. (b) HHI index by sub-sectors. *Source*: Superintendencia de Compañías, Valores y Seguros. *Elaboration*: Authors. [Colour figure can be viewed at wileyonlinelibrary.com]



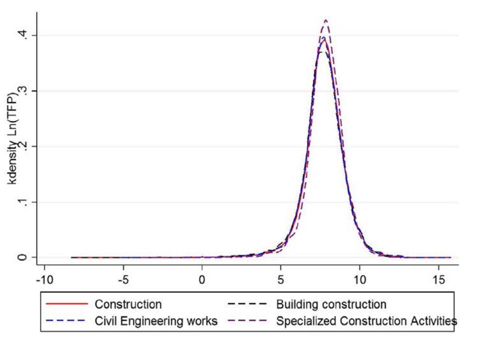
(a) TFP evolution across years



(b) TFP growth and GDP cycle



(c) TFP evolution across years and sub-sectors



(d) TFP Kernel density by sub-sectors

FIGURE 2 TFP dynamic in the construction sector (2007–2018). (a) Average productivity for each year of the period of analysis in natural logarithm. (b) Average growth rate of productivity by year and GDP cycle. (c) Average TFP by construction subsector by year. (d) Kernel density of the natural logarithm of the TFP by construction subsector. The construction category represents the overall industry average estimates. The TFP calculations were obtained from the estimated coefficients in the WDRG estimator for the entire construction sector. *Elaboration:* Authors. [Colour figure can be viewed at wileyonlinelibrary.com] distribution of the productivity in logarithms are presented. Figure 2a shows the evolution of the TFP estimated using the WDRG estimator; Figure 2b shows the relationship between TFP growth and GDP cycle; the figure suggests that these two variables are pro-cyclical since they have the same pattern; in Figure 2c we present the evolution of TFP by subsectors, and we show that the specialized construction activities have larger TFP (in mean) than the other subsectors; more important is that this subsector has a TFP larger than the TFP mean in the whole construction sector. Finally, in Figure 2d we show the TFP kernel density by subsectors, and we show that all subsectors are similar in terms of density.

In Table 2, we show the correlation matrix of our main variables of interest to analyze the determinants of TFP. We show that most of the variables are significantly correlated; nevertheless, the highest correlation is between ROA and dte (–0.260), and it follows by age and size (0.181); there is no evidence to suspect of autocorrelation and heteroscedasticity between the variables used as possible TFP determinants. More important, we show that there is a negative correlation between age and TFP growth but a positive correlation with contemporaneous TFP; also, there is a positive correlation between size and TFP and its growth; something similar is found with ROA and GDP cycle. This preliminary evidence suggests that there are no learning-by-doing effects, size is important in determining productivity, the TFP is pro-cyclical with respect to GDP cycle, and profits are related to TFP.

Figure A.1 shows the evolution of TFP by size. We show that the average TFP of microenterprises is lower than that of the rest of the firms. As expected, large firms have on average the highest TFP. This corroborates that the larger the firms are, the higher productivity they are expected to have.

4 | RESULTS

This section describes the main results obtained from the estimation of the production function (Equation 4) in the construction sector by different estimators and then captures the TFP of our preferred estimator (WDRG) to analyze the determinants of TFP and its growth.

4.1 | Production function and TFP estimation

According to the characteristics of the aforementioned productivity model, in Table 4, we present the results of the coefficients obtained for each of the inputs of the Cobb–Douglas production function estimated by six methods: OLS, FE, GMM-SYS, LP, LP-Ackerberg, Caves and Frazer (ACF), and WDRG.[9]

In addition, we controlled for time-varying unobserved factors, to capture exogenous macroeconomic shocks, such as the impact of the global crisis in the 2008–2009 period, the latest crisis generated by the fall in oil prices in international markets, and the dollar appreciation in the period 2014–2016. We also control for the economic subsector to which each firm belongs, since there are marked differences in the behavior and reported revenue levels, showing intra-sector heterogeneities, aiming to reduce the probability of biases in the estimation of each of the coefficients of production inputs. This control also captures the possible exogenous shocks that could affect each subsector.

We compared different estimation methods to contrast and observe that the estimators have similar results in magnitude and significance. However, as discussed in Section 3.1 all the methodologies have pros and cons, although our preferred method is the WDRG with FE estimator because it corrects the simultaneous determination of inputs and unobserved productivity by proxying the latter with firm-level intermediate inputs and FEs (Caselli, 2018).

TABLE 2 Correlation matrix of TFP determinants

	TFP	TFP growth	Age	FF	ROA	Size	Exports	Imports	dte	Credit	HHI	GDP cycle	Large cities
TFP	1												
TFP growth	0.443*	1											
age	0.146*	–0.090*	1										
FF	–0.085*	–0.012	–0.018	1									
ROA	0.141*	0.162*	–0.126*	0.014*	1								
Size	0.236*	0.035*	0.181*	–0.114*	–0.031*	1							
Exports	0.007	–0.013	–0.048*	–0.075*	0.007	0.076*	1						
Imports	0.005	–0.009*	0.078*	0.004	–0.012	0.082*	0.026*	1					
dte	0.027*	0.063*	–0.157*	–0.025	–0.260*	0.016	0.003	0.001	1				
Credit	0.121*	–0.002	0.147*	0.003	–0.105*	0.124*	–0.010	0.041*	0.100*	1			
HHI	0.015	–0.015	–0.014	–0.024	0.048*	0.056*	0.016	0.001	–0.097*	–0.002	1		
GDP cycle	0.062*	0.039*	–0.025	0.007	–0.019	0.011	0.057*	–0.002	–0.012	–0.004	–0.096*	1	
Large cities	0.098*	0.003	0.179*	–0.028*	–0.059*	0.070*	0.005	0.020	0.075*	0.045*	–0.060*	–0.026*	1

Note: Pearson's correlation coefficients.

Abbreviations: dte = debt-to-equity; FF = family firm; GDP = gross domestic product; HHI = Herfindahl–Hirschman Index; TFP = total factor productivity.

***p <.001.

TABLE 3 Estimation of the production function of the overall construction sector in Ecuador

Y_t	OLS	FE	GMM-SYS	LP	LP-ACF	WDRG
k	0.135***	0.105***	0.045***	0.149***	0.118***	0.106***
	(0.009)	(0.011)	(0.012)	(0.015)	(0.010)	(0.010)
l	0.428***	0.176***	0.113***	0.401***	0.435***	0.450***
	(0.012)	(0.011)	(0.023)	(0.013)	(0.005)	(0.008)
m	0.353***	0.306***	0.265***	0.297***	0.367***	0.283***
	(0.007)	(0.008)	(0.018)	(0.007)	(0.006)	(0.010)
Subsector control[a]	Yes	Yes	Yes	Yes	Yes	Yes
City control[a]	Yes	Yes	Yes	Yes	Yes	Yes
Time control[a]	Yes	Yes	Yes	Yes	Yes	Yes
Wald test Constant Returns to scale (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Sargan test[b]	–	–	0.150	–	–	–
AR(1)[c]	–	–	0.000	–	–	–
AR(2)[c]	–	–	0.868	–	–	–
R^2	0.582	0.323	–	–	–	–
Observations	23,256	23,256	11,869	23,256	23,256	16,341

Note: Estimates at a general level including all subsectors of construction. We use a two-stage GMM-SYSTEM model that treats k as the default and l and m as endogenous. Clustered robust standard errors by firm are in parentheses. The WDRG estimators include FF effects.

Abbreviations: FE = fixed effect; GMM = generalized method of moments; OLS = ordinary least squares.

Elaboration: Authors.

[a]We included dummies that control by the most representative cities (Guayaquil, Quito, and Cuenca), by years, and by economic subsectors according to the classification proposed for the construction sector.

[b]The Sargan test presents the p-value for the validation of the null hypothesis that all overidentifying restrictions are valid.

[c]AR(1) and AR(2) present the p-values for the validation of autocorrelation of first and not autocorrelation of second order, necessary in the GMM-SYS. The instruments estimated for GMM-SYS are lagged logarithmic differences of k, l, and m with lags in levels $t-1$ and $t-2$.

*p <.1; **p <.05; ***p <.01.

The results presented in Table 3 are those estimated for the entire construction industry. We show in all the estimators that the capital input has the lowest elasticity. Moreover, when we analyze only the semiparametric estimators (LP, LP-ACF, and WDRG), we find that the labor input is the greatest, implying that this industry is labor intensive. In addition, we test if there are constant returns to scale and find that there are no such returns, and indeed, the evidence suggests the presence of decreasing returns to scale in the industry.

In Table 4 we present the correlation matrix between the six measures of productivity based on the estimation of the production function in Equation 4. We show that the correlation is positive and significant at the 1% level, except for the LP and WDRG estimators. The correlation ranges between 0.10 and 0.92 and tends to be lower for the semiparametric estimators. These differences in productivity are based on the different assumptions of each estimator, particularly in the endogeneity of the input's usage. However, we prefer the WDRG estimator because it assumes that labor and intermediate inputs

TABLE 4 Correlation between different estimates of productivity

	OLS	FE	GMM-SYS	LP	LP-ACF	WDRG
OLS	1					
FE	0.897*	1				
GMM-SYS	0.857*	0.924*	1			
LP	0.102*	0.224*	0.305*	1		
LP-ACF	0.240*	0.207*	0.204*	0.357*	1	
WDRG	0.459*	0.383*	0.349*	0.007	0.120*	1

Note: Pearson's correlation coefficients.

Abbreviations: FE = fixed effect; GMM = generalized method of moments; OLS = ordinary least squares.

***p <.001.

TABLE 5 Estimation of the production function for the subsectors of the construction industry

Y_t	(1) Building construction	(2) Civil engineering works	(3) Specialized construction activities
K	0.070***	0.161***	0.089***
	(0.013)	(0.015)	(0.032)
l	0.463***	0.351***	0.530***
	(0.011)	(0.017)	(0.019)
m	0.280***	0.322***	0.218***
	(0.014)	(0.018)	(0.025)
City control[a]	Yes	Yes	Yes
Time control[a]	Yes	Yes	Yes
Wald test Constant Returns to scale (p-value)	0.000	0.000	0.000
Observations	7,575	5,401	3,357

Note: Clustered robust standard errors by firm are in parentheses. The WDRG estimators include firm-fixed effects.

Elaboration: Authors.

[a]We included dummies that control by the most representative cities (Guayaquil, Quito, and Cuenca) and by years.

*p <.1; **p <.05; ***p <.01.

are endogenous and can be instrumented by their lagged values and that a second-order polynomial in lagged capital and intermediate inputs can be used as a proxy for productivity[10] (Caselli, 2018).

In addition, we estimate the production function by using the WDRG estimator for each of the economic subsectors within the construction industry and present the results in Table 5. We show that there is a heterogeneity effect of each input on production; in particular, we find that the elasticity of capital input varies across subsectors but always has the lowest elasticity compared with intermediate inputs and labor. Again, we find that the highest elasticity of inputs is from labor input, showing that all three subsectors are labor intensive. More important is that all inputs are different across subsectors, meaning there is an important source of heterogeneity in the input usage. There is no evidence of constant returns to scale in any of the three subsectors, and similar to the entire construction sector, the evidence suggests that indeed there are decreasing returns to scale, which could mean that there is an inefficient management of productive resources.

4.2 | Factors that influence productivity in the construction sector

Once the TFP is estimated by Equation 4 using the WDRG estimator, we recover the TFP using Equation 5, and we continue with the analysis of its determinants in the second stage. For this, we estimate Equations 6 and 7 for all the construction sector and their three subsectors using the poled ordinary least square (POLS) methodology to account for yearly and geographical heterogeneity since not accounting for heterogeneity effects can lead to endogeneity issues; we use GDP cycle and geographical location to control possible external effects.

We analyze different internal firm characteristics, international trade activities, financial constraints, and external characteristics that could be related with TFP and its growth (these variables are discussed in Section 3.2).[11] In Table 6, we show the coefficients obtained for each of the variables analyzed in the POLS model with robust standard errors grouped by firms.

According to the internal firm characteristics, we have a consensus in our results for our four variables (age, FF, ROA, and size) across the three construction subsectors. Our evidence suggests that age is positively related with contemporaneous TFP but is negatively related with TFP growth; this result is consistent with the hypothesis that younger firms produce with greater efficiency and better technology than older firms (Ding et al., 2016), allowing them to have a higher growth rate of the TFP. Moreover, the learning-by-doing hypothesis is not supported, because as a firm gets older the effect is positive only in year *t*, suggesting that the marginal effect on TFP level is decreasing. Also, we show that being a FF is negatively related with TFP and its growth, but it is significant only with the TFP level; this suggests that FFs are less productive than their counterparts maybe because decisions are constrained by their owners' time (Bloom et al., 2010). In terms of profitability, our results suggest that ROA is positively related with TFP and its growth; more profits increase productivity because firms could invest in more technology or human resources. The evidence of firm size is similar, corroborating the findings of several authors who argue that the larger the firm is, the higher productivity it has.

In addition, regarding international trade activities, our results are ambiguous because we find that exports are significant and negatively related with TFP only in the building construction subsector and negatively related with TFP growth in the civil engineering works subsector; nevertheless, it is positively related with TFP level in the specialized construction activities subsector. This result could be since only 2.5% of firms in the construction industry export. Moreover, in terms of imports, we find that it is negatively related with TFP and its growth in the entire construction sector; the evidence is not significant at standard levels for the subsectors, with the exception for specialized construction activities where imports are negatively associated with TFP.

According to financial constraint variables, we find a consensus that debt and access to credit are related with an increase in TFP and its growth in the entire construction sector and many subsectors. In particular, debt-to-equity (dte) is positively related with TFP and its growth in all the subsectors, and also credit is positively related with TFP. This evidence supports the idea of Van Biesebroeck (2005) who found that firms that receive any kind of credit have higher productivity levels than firms that do not receive credit.

Finally, we analyze three external characteristics such as HHI index for competition effects, GDP cycle for macroeconomic effects, and being in a large city for geographical location effects. Our results suggest that an increase in market concentration (HHI) is negatively related with TFP in the whole construction sector and in the specialized construction activities subsector; nevertheless, it is positively related with TFP and its growth only in the building construction subsector; this result is unexpected, but in all the industry there is evidence in favor of the hypothesis that efficiency increases within plants or firms; in this mechanism competition can induce firms to take up expensive

TABLE 6 Determinants of productivity across the construction sector in Ecuador

	Construction		Building construction		Civil engineering works		Specialized construction activities	
	TFP	TFP growth	TFP	TFP growth	TFP	TFP growth	TFP	TFP growth
Internal firm characteristics								
Age	0.147***	–0.058***	0.141***	–0.079***	0.115***	–0.034*	0.242***	–0.063***
	(0.016)	(0.011)	(0.025)	(0.019)	(0.025)	(0.019)	(0.033)	(0.021)
FF	–0.326***	–0.051	–0.248***	–0.098*	–0.440***	–0.007	–0.251*	–0.044
	(0.058)	(0.034)	(0.080)	(0.058)	(0.092)	(0.055)	(0.135)	(0.066)
ROA	1.924***	2.080***	1.957***	1.963***	2.036***	2.446***	1.813***	1.773***
	(0.128)	(0.117)	(0.185)	(0.171)	(0.237)	(0.225)	(0.218)	(0.196)
Size	1.049***	0.200***	1.268***	0.176***	0.955***	0.264***	0.838***	0.113**
	(0.079)	(0.025)	(0.119)	(0.045)	(0.132)	(0.040)	(0.122)	(0.052)
International trade activities								
Exports	–0.016	–0.073	–0.221*	–0.019	–0.146	–0.268**	0.508***	0.074
	(0.074)	(0.061)	(0.120)	(0.129)	(0.129)	(0.112)	(0.096)	(0.083)
Imports	–0.365***	–0.087*	–0.126	–0.102	–0.356	–0.096	–0.326***	–0.047
	(0.078)	(0.050)	(0.112)	(0.113)	(0.435)	(0.135)	(0.103)	(0.055)
Financial constraints								
dte	0.073***	0.105***	0.085***	0.102***	0.026	0.105***	0.139***	0.108***
	(0.011)	(0.010)	(0.015)	(0.014)	(0.020)	(0.016)	(0.030)	(0.020)
Credit	0.266***	0.016	0.289***	0.015	0.192***	–0.023	0.303***	0.074**
	(0.021)	(0.018)	(0.033)	(0.029)	(0.035)	(0.029)	(0.040)	(0.032)
External characteristics								
HHI	–0.111***	–0.023	0.166***	0.175**	–0.048	–0.195***	–0.374***	0.029
	(0.031)	(0.033)	(0.057)	(0.069)	(0.056)	(0.066)	(0.064)	(0.047)
GDP cycle	4.789***	3.273***	7.131***	5.194***	5.166***	3.578***	2.652***	3.636***
	(0.472)	(0.471)	(0.849)	(0.918)	(0.870)	(0.814)	(0.897)	(0.868)
Large cities	0.177***	0.007	0.132***	–0.008	0.255***	0.019	0.116	0.021
	(0.030)	(0.017)	(0.043)	(0.025)	(0.045)	(0.026)	(0.101)	(0.046)
Subsector Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.116	0.048	0.106	0.043	0.140	0.064	0.197	0.060
Observations	21,096	15,128	9,927	6,988	7,115	4,999	4,054	3,141

Note: Time controls are not included because the GDP cycle captures the cyclical effect of the economy and exogenous shocks that may have existed in this period. Clustered robust standard errors by firm are in parentheses.

Abbreviations: dte = debt-to-equity; FF = fixed effect; GDP = gross domestic product; HHI = Herfindahl–Hirschman Index; TFP = total factor productivity.

*p <.1; **p <.05; ***p <.01.

productivity, leading to actions that they may otherwise not do (Syverson, 2011). With respect to GDP cycle, our findings have similar effects on TFP and its growth; there is positive and significant evidence that TFP and its growth are pro-cyclical across the construction sector. Finally, we find that being located in one of the three most important cities in Ecuador is positively related with TFP but not for its growth in the entire construction sector and in the three subsectors.

Overall, our results suggest that younger firms perform better than older firms, but more important is that there are no learning-by-doing effects. Being a large firm and having higher profits are important determinants of productivity. Nevertheless, being an FF has negative effects on TFP. International trade activities have ambiguous results, but better access to debt (*dte* or *credit*) has positive effects on TFP and its growth. Finally, more competition, better GDP cycle, and being located in an important city have positive effects on productivity.

5 | CONCLUSIONS

This paper analyzes the determinants of TFP in the Ecuadorian construction sector during the period 2007–2018. Thus, we estimated a traditional production function of the Cobb–Douglas style through parametric and semiparametric estimators. The former estimators are obtained to solve the endogeneity issues in the input usage. We prefer the Wooldridge (2009) estimator with FEs. After the production function estimation, we recover the TFP to analyze the determinants of a large set of covariates that are grouped in internal firm characteristics, international trade activities, financial constraints, and external characteristics.

Overall, our results suggest a consensus that firm age is positively related with TFP but negatively related with TFP growth across the construction subsectors; this evidence is consistent with the finding that younger firms perform better than older firms, but it is not in favor of the learning-by-doing hypothesis. Another finding in our analysis is that being an FF is negatively related with TFP, but size is positively related with TFP and its growth across the construction subsectors. We do not find a clear relationship between being in international markets and TFP across the subsectors analyzed, but we find that import intermediate inputs are negatively related with TFP and its growth in the entire construction sector. Moreover, we find that access to debt and credit is positively related with productivity, but operating in less-competitive environments is negatively related with it. Another result suggests that reduced competition in markets could discourage innovation processes and improvements to capture demand and therefore reduce TFP. Finally, our results suggest that TFP and its growth are pro-cyclical with respect to GDP as suggested by Crawford and Vogl (2006) and Zhi et al. (2003).

Our results have several managerial implications. First, as we found that there are no learning-by-doing effects, firms are required to prepare more innovative processes to avoid the "wear-and-tear" effect and because new capital embodies the latest technology (Harris & Moffat, 2015). Second, as being an FF has negative effects on TFP, it is necessary to start opening the ownership of capital or delegating the managerial decision to people who are out of the family. Third, although our results do not show clear evidence of the effect of international trade, it is well known that it drives production, so starting to export and import less would be a good decision. Finally, access to credit and debt has a positive effect on productivity; however, care must be taken with indebtedness since excessive indebtedness could generate liquidity problems, and therefore, the purchase of productive inputs can be compromised.

Our results have certain limitations due to the nature of the administrative data, and it would be preferable to have data of quantities and not in currencies. Although several authors have shown that this is not as serious a problem as it appears to be, this could be a limitation of the study. In addition, having more internal features will always be important to reduce possible unobserved effects.

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DATA AVAILABILITY STATEMENT

We do not have permission to share the data, but they are available to researchers on request to the SCVS.

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ENDNOTES

[1] See, for example, Harris et al. (2005), Loosemore (2014), and Harris and Moffat (2015).

[2] A family firm in this case is defined as one that has more than 50% of the capital owned by a family group.

[3] According to the Inter-American Developing Bank, in the Latin American region approximately 41% of firms do not have a line of credit or loan from a financial institution (Inter-American Investment Corporation [IIC], 2020).

[4] See the "Methodology" section for more details.

[5] This is the case of the Ecuadorian construction industry, where only 5% of formal firms report values of investments.

[6] Many authors use the same two-stage approach in which they first estimate the production function and then they analyze the TFP determinants (see, e.g., Gatti & Love, 2008; Harris et al., 2005).

[7] Supervisory and Regulatory Agency of formal firms in Ecuador.

[8] Nonconcentrated markets: HHI below 1,500 or 15%; moderate concentrated markets: HHI between 1,500 and 2,500 or 15% and 25%; highly concentrated markets: HHI above 2,500 or 25%.

[9] In the estimations of the production function by LP, LP-ACF, and WDRG, we use the command *prodest* proposed by Rovigatti and Mollisi (2018).

[10] This is the reason why the number of observations drops if we compare to the alternative estimators.

[11] We do not analyze the dynamic effect of productivity because when the TFP is recovered from WDRG estimator, the law of motion of productivity is affected, and the lag effect is also included in the contemporaneous value.

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APPENDIX

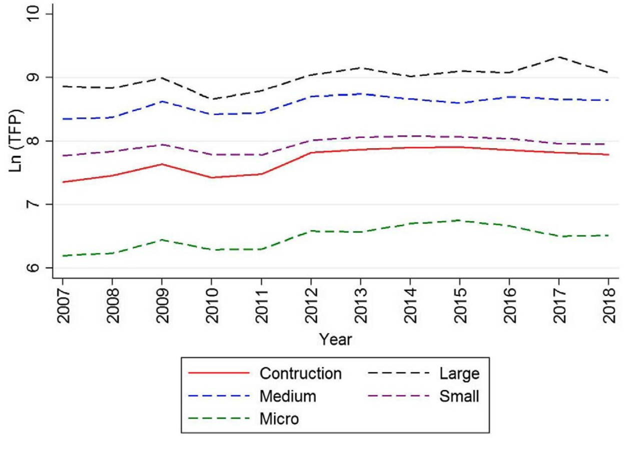

FIGURE A1 Average TFP by size
Elaboration: Authors. [Colour figure can be viewed at wileyonlinelibrary.com]