Technical efficiency, technology and investment decisions in mexican manufacturing firms

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Abstract

We study how technical efficiency and technology may explain investment decisions of Mexican manufacturing firms. We use DEA technical efficiency measures, technological structure indicators and OLS regressions to develop the study. The analysis uses cross-sectional census data. Our results suggest that technical efficiency may encourage investment. The statistical relevance of technological structure determinants seems somewhat weak. The results also show that high-technology manufacturing micro firms invest more than other ones. Furthermore they suggest that capital-only technical efficiency measures may be useful determinants of investment decisions. Indeed capital seems a more relevant input than labor.

Keywords: Investment, technical efficiency, technology, manufacturing, Mexico

TECHNICAL EFFICIENCY, TECHNOLOGY AND INVESTMENT DECISIONS IN MEXICAN MANUFACTURING FIRMS

1. Introduction

Investment decisions are central to our understanding of economic activity. Firms´ performance, technological innovation and economic growth depend on investment decisions. Particularly, development economists support the view that investments in the manufacturing industry are essential to encourage the industrialization of underdeveloped economies [see Nurkse (1953) and Lewis (1954)]. Such relevance explains why several research efforts have been developed to explain the determinants of the formation of fixed capital. Such efforts manifest themselves not only in theoretical and empirical studies, but also in studies from the macro and microeconomic perspectives.

From a microeconomic perspective, technology imposes constraints to firms´ behavior and their decisions. Such consideration explains why one of the main issues addressed in the literature on investment refers to the characteristics of technology [Chirinko (1993)]. Theoretically, the technology available to a firm is described with its production set and the production function. The production set includes all the combinations of inputs and outputs that are technologically feasible. The production function describes the boundary of such production set. When a firm produces the maximum output from the minimum quantity of inputs (i.e. along its production function), it is considered as technically efficient.

In practice technical efficiency is measured with the Data Envelopment Analysis (DEA) methodology. The methodology evaluates and compares the performance of various decision-making units (DMU´s), like firms, industries or organizations [Charnes, Cooper and Rhodes (1978)]. DEA concerns with measuring the relative efficiency of the various DMU´s as they transform their inputs into outputs. The DEA methodology uses linear programming methods to estimate non-parametric frontiers (in other words, production function approximations), from observed data. The methodology also identifies efficient production units, which belong to the estimated frontier, and inefficient ones, which remain below it.

Here we study the econometric relationships among technical efficiency, technology and investment decisions in a developing economy. We analyze such relationships for the Mexican manufacturing firms. Particularly, we assume that technology and efficiency determinants may constrain their investment decisions. We use several DEA technical efficiency measures and technological structure indicators to assess the determinants of investment. In addition we include certain firms characteristics (size dimension, cash flow and investment opportunities), as control variables. We develop the study with cross-sectional data of the last manufacturing census available for the Mexican economy.

This investigation aims at suggesting answers to some questions regarding the relationships among technical efficiency, technology and investment. These questions are the ones that define the scope and limits of our study. These questions are the following: What are the stylized facts regarding the technical efficiency-technology relationship? How technical efficiency and technology determinants may influence investment decisions? What technical efficiency measures may be the most relevant ones? Does technological structure matter? What firms´ characteristics may be important to understand investment decisions? Which type of implications may be derived from these findings?

We follow several steps to develop this econometric study. First, we build the independent variable, assortments of indicators and control variables with cross-sectional data. In addition we describe certain stylized facts regarding the technical efficiency-technology relationship to contextualize the analysis. Then we assess the relationships among technical efficiency, technology and investment decisions with three sets of OLS regressions. In all the assessments, we control for the effects of firms´ characteristics (cash flow, firm size and investment opportunities). Finally, we use several statistical tests to check the robustness of our results.

Academically, our study has some distinctive features that differentiate it with respect to other studies. The first one is that the investment-determinant assessment focuses on the manufacturing firms of a developing economy. Most studies focus on developed ones. A second feature is that it analyzes the 182 industries of the manufacturing sector. Traditional studies usually focus on a single or a small group of the industries. The third one is that the assessments use simultaneously efficiency and technology determinants. Finally the last feature of our study is that we control for the effects of certain firms characteristics. Such controls are introduced for consistency with other studies.

We should point out that our study also complements other econometric studies for the Mexican manufacturing firms. Particularly it complements the studies of Ito (2010) and Padilla and Guzman (2010). The first study focuses on the effects of NAFTA on productivity convergence. Not surprisingly, the first study mentions that "because of the limited availability of data, the panel data cover 18 manufacturing industries for 15 years (1986-2000)" [Ito (2010:22)]. The second study focuses on the determinants of regional manufacturing growth for the period 1993-2007. Both studies use variations of the TFP (Total factor productivity) methodology to develop the econometric assessments.

The paper is organized as follows. Section 2 reviews the literature. Section 3 describes the methodological design of the research. We describe the sources of data and the variables and indicators. Furthermore we describe the econometric modeling and testing procedures. Section 4 shows the outcomes of the econometric study. The section shows the stylized facts regarding the technical efficiency-technology relationship. Then it shows the econometric results and their analysis. The section concludes with the statistical tests that support the empirical assessment. Section 5 summarizes and discusses the main findings. Finally, the appendix focuses on the mathematical details of the technical efficiency estimations.

2. Technology, efficiency and investment decisions

Contemporary economics suggests that economic performance relies on technological change and investment decisions [Greenwood, Hercowitz, and Krusell (2000)]. Historians and macroeconomists place them at the center of the economic development process. Indeed the modern endogenous growth literature explains per capita growth on the basis of technology and investment decisions are complementary processes [See Barro and Sala-i-Martin (2003)]. Moreover, it provides policy recommendations for developing economies. For example, Casares (2007) suggests that the promotion of manufacturing industries may be necessary to induce productivity, structural changes and economic growth.[1]

Traditional development economists also argue that technology and investment in the manufacturing sector are necessary to encourage economic growth. Most of them believe that the "vicious circle of poverty", that characterizes developing economies, can be broken by investing in the manufacturing sector [see Nurkse (1953) and Lewis (1954)]. These views are supported by the study of Lall (2000). Such study argues that the technological structure prevailing in manufacturing firms have implications for growth and development. Moreover, he proposes a classification system to describe the technological structure of export-oriented manufacturing industries of developing economies.

Paradoxically, there is no consensus regarding the causality of the technology-investment relationship. Usually, it depends on the level of aggregation of the analysis. Traditional macroeconomic theories assume that investment induces externalities and channels innovation (and technological change) [Chirinko (1993)]. However, other studies assume that causality runs in the opposite direction [Greenwood, Hercowitz, and Krusell (2000)]. Post-keynesians assume bidirectional causality [Cortez (2007)]. From a microeconomic perspective, controversies do not exist: Technology imposes constraints to firms´ behavior [Varian (1993)]. Thus, technology explains investment decisions at least in the short-run.

Here we argue that firms are constrained by the technology available and by their efficiency to transform inputs into outputs. Moreover, we assume that technology and efficiency issues are closely linked. We adopt such assumption on the basis that the technological

[1] The theoretical findings of Casares (2007) have support on the findings of Schiff and Wang (2003). The latter authors find macroeconomic evidence on the relationship between technology diffusion and productivity using data of certain Mexican manufacturing industries. Their study follows the guidelines of the traditional endogenous growth literature.

constraints of a firm define its production set and its production function [Varian (1993)]. Particularly, when the inputs and outputs of a firm are explained by its production function, the firm is considered as technically efficient. Technical efficiency is a condition necessary for optimization. Thus it should explain firms´ decisions. Particularly, we assume that investment decisions may depend on technical efficiency even when firms are not fully efficient.

However, the measurement of technical efficiency is very restrictive. Usually production functions are unknown. In practice, economists rely on a "somewhat less satisfactory concept of `relative efficiency´ [Charnes, Cooper and Rhodes (1978:430)]. Data-Envelopment-Analysis (DEA) is a methodology for measuring the relative efficiency of various decision-making units (DMU´s), like firms, as they transform their inputs into outputs. The DEA methodology estimates relations from observed data using programming techniques. Its main advantages are that it does not require or assume any functional relationship among the inputs and outputs, and that it connects engineering and economic approaches to efficiency.

Methodologically, the technical efficiency measures are calculated with respect to technological benchmarks represented by a frontier function. The DEA methodology calculates such function by "finding the segments that envelope" all the DMU´s performances [Murillo- Zambrano (2004)]. The efficiency measures depend on different assumptions regarding the frontier functions. Three well-known efficiency measures are the ones proposed by Banker, Charnes and Cooper (1984). These are the Global Technical Efficiency (GTE), the Pure Technical Efficiency (PTE) and the Scale Efficiency (SE) measures. These are the standard measures of technical efficiency in the literature.

The technical efficiency measures describe different aspects of the effectiveness with which a given set of inputs is used to produce outputs. The GTE and PTE measures characterize the relative efficiencies of specific DMU´s with respect to frontier functions defined by constant-returns-to-scale (CRS) and variable-returns-to-scale (VRS), respectively. When these measures are equal to one, the production unit is considered technically efficient. Otherwise, there is some degree of technical inefficiency. The SE measure can be interpreted as the additional increase in the production of outputs if the technology were to present constant returns to scale at the point where the productive unit evaluated is located.

Efficiency studies based on DEA methodologies have been used extensively to analyze different organizations and industries [see Emrouznejad, Parker and Tavares (2008) for a review]. However DEA studies for the firms of developing economies are relatively scarce. Moreover, few of them are oriented to manufacturing firms. Some recent studies are Söderboom and Teal (2004), Brown and Dominguez (2004), Padilla and Guzmán (2010) and Ito (2010). The first study focuses on the impact of firms´ size for input decisions in

Ghana. The others analyze productivity issues in Mexico. Despite their importance, none of these studies for developing economies measures the impact of efficiency on investment decisions.

Econometric studies on the technological determinants of investment focus on developed economies. Some of these investment-determinant studies are reviewed by Chirinko (1993) and Carruth, Dickerson and Henley (2000). Recent studies are the ones of Naboulet and Raspiller (2006) and Bontempi, Golinelli, and Parigi, (2010). The first study finds a positive relationship between technology and investment for French firms. The second one focuses on the effects of the irreversibility of production functions and labor flexibility on Italian manufacturing firms. Neither of these studies focuses on efficiency issues. Thus the study of these determinants remains as an area relatively unexplored for developing economies.

We conclude by emphasizing that the study of the relationships among technical efficiency, technology and investment decisions seem relevant for developing economies. Such study seems necessary to encourage economic growth and development. Here we study such relationships in the context of the Mexican manufacturing firms. We develop such study on the basis of the microeconomic theory of technology. Methodologically we use the DEA methodology and OLS regression techniques to develop the study. Furthermore, we control by certain firms characteristics. Such controls are introduced for consistency with other investment-determinant studies. Such study is developed in the following sections.

3. Methodology

In this section we describe the methodological design of our investigation. Specifically, we describe the sources of data and the variables and indicators. We focus on the methodological assumptions that allow us to build the variables used in the assessments. Such variables include the manufacturing firm variables, the technical efficiency and technology determinants and the control variables. Furthermore, we describe the econometric modeling and testing procedures used in the assessments. The relevance of such descriptions relies on the fact that they define the scope and limitations of our study.

3.1 Data sources

We use data of the Mexican manufacturing firms obtained from the "Economic Census 2004" reported by the Bureau of Statistics (known as INEGI). Methodologically, the census is constructed accordingly to the North-American-Industry-Classification-System (NAICS). It includes 12 classificatory groups of firms for each of the 182 industries. We use this cross-sectional data set because previous censuses are built with non-comparable methodologies.

In Mexico, firm-level data are not available due to confidentiality reasons. We deal with such constraint by constructing a set of four groups of representative firms (DMU´s) for the 182 industries included in the census. We build the representative firms accordingly to the number of employees. A micro firm has no more than 10 employees. A small firm has between 11 and 50. A medium firm has between 51 and 250. A large firm has at least 251 employees. This simplified system follows the one of the Mexican Economics Ministry.

We build each DMU variable in order to describe the behavior for the decision-making unit of size “j” of industry “i”. We estimate weighted variables to assess the effects of the size of the firms according to the simplified classification system. We use as weight the mean of the number of employees by each type of firm. Each DMU variable is calculated as follows:

$$P_{ijt} = \frac{n_{ijt} M_{jt}}{\sum_{t} n_{ijt} M_{jt}}$$

$$i = 1, \ldots, 182$$

$$j = 1, 2, 3, 4$$

$$t = 1, \ldots, 12$$

(1)

where P_{ijt} is the weighted indicator of the industry “i”, size “j”, group “t”; n_{ijt} is the number of firms of the industry “i”, size “j”, group “t”; M_{jt} is the mean of the number of employees of size “j” in group “t”; the subindex “i” refers to the i-th industry; the subindex “j” refers to the firm of size “j” (micro, small, medium and large firms); the subindex “t” refers to the t-th groups included in the size-j classification.

We build the representative firm variables for all the independent and dependent indicators. We use the weighted indicator of each one of the four decision-making units of industry i to estimate each variable. We multiply P_{ijt} by each variable included in the census classification for each one of the twelve groups of firms V_{ijt}. Such multiplications added accordingly to each subindex “t” provide us with a variable for each DMU of size “j” of the industry “i”.

$$RF_{ij} = \sum_{t} P_{ijt} V_{ijt}$$

$$i = 1, \ldots, 182$$

$$j = 1, 2, 3, 4$$

$$t = 1, \ldots, 12$$

(2)

where RF_{ij} is a variable associated to the decision-making unit of the industry “i”, size “j”; P_{ijt} is the weighted indicator of the industry “i”, size “j”, group “t”.

3.2 Variables and indicators

Here we describe the variables and indicators used in our econometric study. However, before proceeding, we must make certain methodological clarifications. Specifically we assume an output-orientated modeling approach to estimate the measures of technical efficiency.[2] In addition, we assume three different types of frontier functions to estimate the efficiency measures: The first two types assume only one input; while the third assumes two inputs. Thus, we estimate three types of frontiers and efficiency measures (capital-only, labor-only and capital-and-labor, respectively). Furthermore, the control variables include cash flows, investment opportunities and firms´ size.

Methodologically, we define nine indicators to describe the relationships among efficiency, technology and investment. We organize them in three assortments of indicators. The *efficiency-assortment* includes measures of Global Technical Efficiency (GTE), Pure Technical Efficiency (PTE) and Scale Efficiency (SE). Mathematically, the GTE and PTE measures are the output-orientated technical efficiency scores obtained from solving the programming models that define the DEA methodology. Here we should point out that the adequacy of both measures is supported by the use of the multi-stage DEA approach [see Coelli, et. al. (2005)].[3] The third measure is the GTE-over-PTE ratio.[4]

The *technology-assortment* includes three dummy indicators that characterize manufacturing industries as resource-based, low technology, medium technology and high technology ones. Methodologically, we use the technology classification system proposed by Lall (2000) to describe the technological structure of export-oriented manufacturing industries. The assortment focuses on the types of products manufactured by the representative firms. Econometrically, we should point out that the assortment is integrated by three indicators to avoid multicollinearity problems (the “dummy variable trap”). Particularly, we use the group of resource-based industries as the reference group for econometric purposes.

We include certain control variables to complement the previous indicators. Specifically we use variables for firm size, cash flow and investment opportunities. These are variables commonly used in the investment-determinant literature. For example, Adelegen and Ariyo (2008) and Bokpin and Onumah (2009), use firm-size and cash-flow variables in their investment-determinant studies of manufacturing firms. Furthermore, the opportunities-investment variable that we use is the one proposed by Bøhren, Cooper and Priestley

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[2] The DEA literature uses two modeling approaches to study efficiency issues. These are the input-oriented and the output-oriented models. From a mathematical perspective, both types of models estimate the same frontier and identify the same set of efficient DMU´s. However, the efficiency measures associated with the inefficient DMU´s may differ accordingly to the orientation chosen. See Coelli, et. al., (2005), for descriptions and comparisons of both types of models.

[3] We use the DEAP software version 2.1 to estimate the efficiency measures.

[4] Notice that $PTE \geq GTE$. This condition implies that $0 \leq SE \leq 1$.

(2007). We use it because it includes the same information as the Tobin's marginal q variable, the traditional measure of investment opportunities. The set of variables and indicators is summarized in Table 1.

Table 1: Variables and indicators

Indicator	Definition	Measures
Dependent Variable		
Investment	Gross fixed capital formation	Investment decisions
Variables used for the DEA estimations		
Capital	Total value of fixed assets minus gross fixed capital formation	Capital as factor of production
Labor	Number of employees	Labor as factor of production
Production	Total production	Output
Efficiency-Assortment Indicators		
Capital efficiency	Measure of relative efficiency of capital according to the DEA method	Efficiency of capital
Labor efficiency	Measure of relative efficiency of labor according to the DEA method	Efficiency of labor
Capital-and-labor efficiency	Measure of relative efficiency of capital and labor according to the DEA method	Joint efficiency of the factors of production
Technology-Assortment Indicators		
Low technology	Dummy variable on the type of products manufactured (Low technology=1; Otherwise=0)	Low technology firms
Medium technology	Dummy variable on the type of products manufactured (Medium technology=1; Otherwise=0)	Medium technology firms
High technology	Dummy variable on the type of products manufactured (High technology=1; Otherwise=0)	High technology firms

Control Variables		
Investment-opportunities	Ratio of production value to fixed capital stock	Investment opportunities
Cash-flow	Net earnings	Liquidity
Firm-size	Total value of fixed assets	Size of the representative firm

Notes: The table shows the variables and indicators used in the study. The dependent variable is investment. The independent variables aim to capture the main features of technology and efficiency. The variables and indicators are built with data from the Economic Census of INEGI (Mexican Bureau of Statistics).

3.3 Modeling specification and econometric techniques

Methodologically, we use three sets of regressions to describe the relationships among technical efficiency, technology and investment and investment decisions. Each regression set uses a specific type of technical efficiency measures. The first regression set uses efficiency measures estimated on the assumption that the frontier functions require capital as the only input. The second set uses measures estimated on the assumption that the frontier functions require solely labor. The third set uses measures estimated on the assumption that the frontier functions require capital and labor as inputs. Each set is integrated by twelve regressions. Thus we estimate thirty-six regressions.

Each regression set is divided in four subsets. Each regression subset focuses on the determinants of investment for a specific type of DMU (micro, small, medium and large). The regressions of each subset use specific measures of technical efficiency. The first regression of each subset uses the GTE indicator. The second regression uses the PTE one. The last regression uses the SE indicator. All the regressions include the dummy indicators of the technology-assortment and the control variables. Thus, each regression is specified as:

$$I_{ij} = \beta_1 + \beta_2 TE_{ij} + \beta_3 D_{ij}^{Low} + \beta_4 D_{ij}^{Medium} + \beta_5 D_{ij}^{High} + \beta_6 C_{ij}^{CF} + \beta_7 C_{ij}^{FS} + \beta_8 C_{ij}^{IO} + \varepsilon_{ij} \qquad (3)$$

where I_{ij} is the investment indicator; TE_{ij} is a technical efficiency indicator; D_{ij}^{Low} is the dummy variable for low-technology industries; D_{ij}^{Medium} is the dummy variable for medium-technology industries; D_{ij}^{High} is the dummy variable for high-technology industries; C_{ij}^{CF} is the cash-flow control variable; C_{ij}^{FS} is the firm-size control variable; C_{sj}^{IO} is the investment-opportunities control variable; and ε_{ij} is the random error term. [5]

[5] We use log transformed variables for the econometric assessments (except for the dummy ones). We use the log transformation because $\hat{\beta}$ coefficients can be interpreted as elasticities of investment with respect to each determinant. Furthermore, the log transformation reduces the possibility of heteroscedasticity problems.

We use the Ordinary-Least-Squares (OLS) technique to develop the regression analysis. Statistically the OLS technique provides us the best linear unbiased estimators under certain assumptions. Such assumptions include: 1) Linearity of the parameters; 2) Normality of errors, $\varepsilon_{ij} \sim N(0, \sigma^2)$; 3) Homoscedasticity, $VAR[\varepsilon_{ij}] = \sigma^2$; 4) No specification bias in the model; and 5) No perfect multicollinearity. Here we support the adequacy of the OLS technique and the robustness of our results with several statistical tests. Such tests include the Jarque-Bera, the Breuch-Pagan and the Ramseys´ RESET ones. Furthermore we use the Restricted-Least-Squares technique to assess the joint significance of the determinants.

4. Empirical assessment

In this section we show the results of the econometric analysis. We begin by summarizing the technical efficiency measures. We organize these measures on the basis of the assumptions necessary to estimate the efficiency measures and the technological classification proposed by Lall (2000). These assumptions refer to the inputs used to estimate the technical efficiency measures (capital-only, labor-only and capital-and-labor measures). The Lall´s classification refers to the types of manufacturing firms (resource-based, low technology, medium technology and high technology ones). For simplicity we report the average values of the efficiency measures. The measures are summarized in Table 2.

Table 2. Technical efficiency and technology determinants (DEA estimations)

Manufacturing firms	Micro			Small			Medium			Large		
	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE
Capital-only measures												
Resource based	0.052	0.475	0.094	0.390	0.448	0.908	0.125	0.574	0.214	0.256	0.442	0.591
Low technology	0.360	0.607	0.604	0.370	0.525	0.682	0.226	0.533	0.398	0.040	0.467	0.060
Medium technology	0.320	0.467	0.701	0.058	0.319	0.214	0.245	0.407	0.660	0.181	0.400	0.439
High technology	0.047	0.596	0.048	0.379	0.445	0.899	0.379	0.542	0.754	0.595	0.626	0.958
Labor-only measures												
Resource based	0.128	0.296	0.543	0.261	0.305	0.909	0.155	0.242	0.831	0.163	0.203	0.840
Low technology	0.491	0.632	0.781	0.395	0.556	0.753	0.244	0.456	0.629	0.206	0.329	0.749
Medium technology	0.212	0.398	0.612	0.297	0.367	0.833	0.120	0.263	0.502	0.231	0.287	0.847
High	0.3	0.5	0.7	0.4	0.5	0.96	0.28	0.42	0.72	0.29	0.40	0.78

technology	93	65	32	89	11	1	6	9	2	1	2	5
Capital-and-labor measures												
Resource based	0.172	0.499	0.343	0.441	0.485	0.930	0.553	0.607	0.928	0.416	0.519	0.834
Low technology	0.556	0.751	0.746	0.673	0.758	0.896	0.576	0.737	0.791	0.437	0.566	0.801
Medium technology	0.424	0.529	0.834	0.302	0.414	0.740	0.304	0.426	0.760	0.440	0.517	0.884
High technology	0.393	0.611	0.687	0.552	0.569	0.977	0.554	0.671	0.840	0.648	0.710	0.920

Notes: GTE, PTE and SE refer to the measures of global technical efficiency, pure technical efficiency and scale efficiency, respectively. The reported values are the average values of the output-orientated technical efficiency scores of each group of DMU´s. The GTE and PTE measures are estimated under different assumptions. These assumptions refer to the inputs used to estimate the frontier functions and the scale of returns that characterize them, (CRS and VRS, respectively). The SE measure is the GTE-over-PTE ratio.

Table 2 suggests certain stylized facts regarding the technical efficiency-technology relationship: 1) Capital-and-labor efficiency measures show higher levels of average efficiency than capital-only and labor-only measures; 2) PTE measures show higher levels of efficiency than GTE ones; [6] 3) the most technically efficient firms generally are low-technology ones. Indeed the results show that high-technology firms are the most efficient ones only when the firms are large. Thus; 4) technical efficiency and technology are not necessarily positively correlated. We should point out that these findings are generally robust to the size and type of manufacturing firms. Moreover, some of them are consistent with theory and intuition.

Tables (3), (4) and (5) show the main estimation outcomes for the three sets of regressions defined by regression (3). Concretely, Table (3) reports the outcomes for the regressions that use capital-only technical efficiency measures. Table (4) reports the outcomes for the ones that use labor-only efficiency measures. Table (5) reports the outcomes for the ones that use capital-and-labor measures. Furthermore, the tables also report some statistical estimators to assess the adequacy of the regressions and to support the econometric analysis. These estimators are the Jarque-Bera and Breusch-Pagan ones to assess, respectively, the normality and homocedasticity of residuals.

[6] Notice that the constant-returns-to-scale (CRS) assumption implicit in GTE measures is appropriate when all the DMU´s are operating at an optimal scale. Such condition may not be satisfied due to the existence of imperfect competition, corporate governance problems, government regulations and financial constraints.

Table 3. Technical efficiency, technology and investment decisions
OLS regression assessments
(Capital-only technical efficiency measures)

Dependent Variable	Micro			Small			Medium			Large		
	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE
Capital contribution	2.02 (1.20)	2.18* (1.94)	1.35*** (2.61)	-0.63 (-0.3)	1.17 (0.79)	-0.46 (-0.24)	0.24*** (4.26)	2.58** (2.25)	0.41 (0.29)	4.26** (2.28)	2.57* (1.87)	0.24 (0.1)
Low technology manufactures	0.08 (0.09)	0.38 (0.56)	-2.08* (-1.65)	-0.43 (-0.52)	-0.51 (-0.62)	-0.51 (-0.57)	-0.02 (-0.95)	-0.85 (-1.35)	-0.97 (-1.40)	0.32 (0.35)	-0.65 (-0.74)	-0.36 (-0.23)
Medium technology manufactures	-0.95 (-1.20)	-0.65 (-0.98)	-3.07** (-2.54)	-0.77 (-0.74)	-0.44 (-0.55)	-0.89 (-0.56)	-0.04* (-1.91)	-0.70 (-1.12)	-1.29 (-1.52)	-0.88 (-1.05)	-1.09 (-1.31)	-1.01 (-1.11)
High technology manufactures	-0.13 (-0.14)	-0.78 (-0.84)	4.67** (2.22)	-0.33 (-0.31)	-0.34 (-0.32)	-0.35 (-0.33)	-0.07** (-2.32)	-1.13 (-1.36)	-1.15 (-1.09)	-1.83 (-1.4)	-0.68 (-0.6)	-0.32 (-0.21)
Cash flow	-0.23 (-1.31)	-0.20 (-1.14)	-0.21 (-1.21)	-0.09 (-1.13)	-0.09 (-1.15)	-0.09 (-1.09)	-0.01* (-1.86)	-0.12 (-0.99)	-0.15 (-1.25)	0.08* (1.67)	0.09* (1.82)	0.10** (1.96)
Size	1.22*** (6.31)	1.15*** (5.9)	1.27*** (6.63)	1.10*** (10.5)	1.09*** (10.49)	1.09*** (9.79)	0.01** (2.37)	1.11*** (6.66)	1.22*** (7.36)	0.75*** (10.94)	0.71*** (10.2)	0.74*** (10.1)
Investment opportunities	0.49** (2.28)	0.38* (1.71)	0.50** (2.45)	0.62*** (2.99)	0.50** (2.46)	0.59*** (3.32)	0.00 (-0.48)	0.06 (0.19)	0.44 (1.58)	0.46** (2.02)	0.43* (1.73)	0.65*** (2.95)

Constant	-9.39*** (-6.80)	-9.43*** (-7.29)	-7.59*** (-5.9)	-12.15*** (-6.46)	-12.93*** (-7.97)	-11.89*** (-4.06)	-0.07 (-1.19)	-7.23*** (-4.28)	-7.52*** (-3.74)	-4.18*** (-3.25)	-3.38*** (-2.79)	-3.31 (-1.39)
Observations	174	174	174	178	178	178	175	175	175	171	171	171
F	100.85***	102.57***	104.84***	91.64***	92***	91.62***	3.78***	41.63***	39.73***	91.31***	90.15***	87.77***
Prob > F	0	0	0	0	0	0	0.0	0	0	0	0	0
R^2	0.81	0.81	0.82	0.79	0.79	0.79	0.14	0.64	0.62	0.80	0.79	0.79
Jarque-Bera	2.64	3.11	2.89	2.77	1.94	2.36	3.7	4.47	4.48	3.82	4.08	3.75
Prob > χ^2	0.2671	0.211	0.2361	0.2498	0.3794	0.3076	0.1573	0.1087	0.1075	0.1445	0.1276	0.1565
Breusch-Pagan	0.4	2.49	0.96	2.01	1.88	2.5	1.38	0.05	0.99	1.43	1.92	1.46
Prob > χ^2	0.5273	0.1147	0.327	0.1561	0.1707	0.1141	0.2398	0.8198	0.3206	0.2312	0.1662	0.2276

Notes: The dependent variable is investment. GTE, PTE and SE refer to the type of efficiency measures used in each regression. The t-statistics are given in parenthesis. One, two and three asterisks indicate significance levels of 10, 5 and 1 percent respectively.

Table 3 reports the outcomes for the first set of regressions. In six out of twelve cases, the coefficients associated to the technical efficiency measures are positive and individually significant. Furthermore, the coefficients associated to the control variables are mostly positive and individually significant. Interestingly, most of the significant dummy coefficients associated to technology are negative (four out of five). Such finding suggest that resource-based manufacturing firms usually invest more than other ones. However, we should point out that the exception refers to high technology micro firms. Their associated coefficient is positive and significant when the regression includes SE efficiency measures.

Statistically, the goodness-of-fit estimators and complementary tests support the robustness of our results. In most cases, the R^2 estimators are relatively high and the overall significance tests suggest that the all the explanatory variables are necessary. Furthermore, the Jarque-Bera tests do not reject the null hypothesis of normality and the Breusch-Pagan tests do not reject the null hypothesis of homoscedasticity. Thus the regression models seem to explain adequately the relationships among technical efficiency, technology and investment decisions in Mexican manufacturing firms.

Table 4. Technical efficiency, technology and investment decisions
OLS regression assessments
(Labor-only technical efficiency measures)

Dependent Variable	Micro			Small			Medium			Large		
	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE
Labor efficiency	-1.20 (-0.96)	0.42 (0.45)	-1.05* (-1.85)	0.01 (0.5)	-0.21 (-0.18)	0.001 (0.04)	-0.02 (-0.45)	0.01 (0.47)	0.01 (0.35)	0.26 (0.60)	0.39 (0.96)	-0.30 (-0.17)
Low technology	1.21 (1.51)	0.61 (0.83)	0.20 (0.25)	-0.01 (-1.04)	-0.37 (-0.43)	-0.01 (-0.9)	0.01 (0.38)	0.003 (0.13)	0.01 (0.38)	-0.61 (-0.67)	-0.74 (-0.8)	-0.51 (-0.57)
Medium technology	-0.35 (-0.52)	-0.50 (-0.73)	-0.25 (-0.34)	0.00 (-0.21)	-0.54 (-0.69)	-0.002 (-0.16)	-0.01 (-0.64)	-0.01 (-0.63)	-0.01 (-0.37)	-1.11 (-1.31)	-1.14 (-1.35)	-1.03 (-1.22)
High technology	-0.08 (-0.09)	-0.47 (-0.48)	1.78* (1.78)	0.01 (0.58)	-0.27 (-0.24)	0.01 (0.77)	-0.01 (-0.26)	-0.02 (-0.53)	-0.01 (-0.36)	-0.39 (-0.34)	-0.54 (-0.47)	-0.25 (-0.22)
Cash-flow	-0.23 (-1.31)	-0.23 (-1.3)	-0.77*** (-3.89)	0.00 (-0.26)	-0.09 (-1.18)	-0.0004 (-0.28)	-0.01** (-2.48)	-0.01** (-2.37)	-0.01** (-2.48)	0.10* (1.84)	0.09* (1.74)	0.10* (1.93)
Firm-size	1.20*** (6.14)	1.20*** (6.11)	0.44* (1.88)	0.00 (0.33)	1.10*** (10.57)	0.001 (0.38)	0.01** (2.51)	0.01** (2.28)	0.01** (2.49)	0.73*** (10.54)	0.74*** (10.67)	0.74*** (10.09)
Investment-opportunities	0.58*** (2.87)	0.55*** (2.63)	0.66*** (2.75)	0.01** (2.09)	0.59*** (3.26)	0.006** (2.16)	0.02* (1.98)	0.02* (1.84)	0.02** (1.96)	0.63*** (2.90)	0.64*** (2.98)	0.66*** (3.00)

Constant	-8.23*** (-6.24)	-8.68*** (-6.98)	-1.97 (-1.37)	0.07*** (2.83)	-12.43*** (-8.04)	0.07** (2.09)	-0.01 (-0.2)	-0.001 (-0.02)	-0.02 (-0.27)	-2.33 (-1.31)	-2.19 (-1.42)	-2.93* (-1.82)
Observations	174	174	174	178	178	178	175	175	175	171	171	171
F	100.46***	99.92***	13.91***	21.93***	91.6***	24.92***	7.36***	9.52***	8.94***	88.02***	88.4***	87.79***
Prob > F	0	0	0	0	0	0	0	0	0	0	0	0
R^2	0.81	0.81	0.37	0.47	0.79	0.51	0.24	0.29	0.27	0.79	0.79	0.79
Jarque-Bera	2.9	3.38	4.51	2.09	3.62	1.49	4.18	3.99	4.47	4.6	4.51	3.78
Prob >□□^{2}	0.2345	0.1848	0.1048	0.3509	0.1634	0.4748	0.1235	0.136	0.107	0.1015	0.1063	0.1557
Breusch-Pagan	0.2	1.08	2.1	0.96	2.43	1.34	2.01	0.04	0.33	1.94	2.09	1.41
Prob > □^{2}	0.6564	0.298	0.1473	0.3274	0.119	0.2472	0.1567	0.8474	0.568	0.1641	0.1486	0.2342

Notes: The dependent variable is investment. GTE, PTE and SE refer to the type of efficiency measures used in each regression. The t-statistics are given in parenthesis. One, two and three asterisks indicate significance levels of 10, 5 and 1 percent respectively.

Table 4 reports the outcomes for the set of regressions that use labor-only technical efficiency measures. Here, the results show that most of the coefficients associated to the efficiency measures are not individually significant. The same occurs with the dummy coefficients estimations associated to technology. However, the there is an exception for high technology micro firms. Like before, the estimated coefficient is positive and significant for the regression that uses SE efficiency measures. Thus, the evidence suggests that capital-only technical efficiency measures may be better than the labor-only ones. Apparently, the capital input and associated frontier functions matter for modeling purposes.

The estimation of the goodness-of-fit estimators and complementary tests confirm our previous hypothesis regarding the relevance of the capital input. Notice that none of the R^2 values estimated for the second set of regressions is bigger than the ones of the first set. Thus, the evidence suggests that the use of capital-only efficiency measures is statistically better than the use of labor-only ones.

However, we should emphasize that the R^2 estimators for the second set of regressions are relatively high and that the overall significance tests confirm the explanatory variables are necessary. Furthermore, the Jarque-Bera tests confirm normality and the Breusch-Pagan tests accept that residuals are homoscedastic.

Table 5. Technical efficiency, technology and investment decisions
OLS regression assessments
(Capital-and-labor technical efficiency measures)

Dependent Variable	Micro			Small			Medium			Large		
	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE
Capital-and-labor efficiency	-0.01 (-0.01)	0.03 (0.05)	-0.04 (-0.06)	0.02 (0.8)	-0.78 (-0.57)	0.01 (0.31)	0.11** (2.34)	0.05 (1.34)	0.05 (1.1)	1.09* (1.66)	0.76 (1.21)	0.58 (0.58)
Low technology	-0.52 (-0.49)	-0.55 (-0.67)	-0.49 (-0.51)	-0.02 (-1.19)	-0.21 (-0.23)	-0.01 (-0.93)	0.002 (0.09)	-0.002 (-0.07)	0.01 (0.6)	-0.71 (-0.8)	-0.65 (-0.73)	-0.47 (-0.54)
Medium technology	-0.22 (-0.24)	-0.24 (-0.31)	-0.19 (-0.21)	0.0003 (0.02)	-0.60 (-0.77)	-0.0002 (-0.02)	0.01 (0.6)	-0.003 (-0.16)	-0.003 (-0.15)	-1.25 (-1.47)	-1.11 (-1.32)	-1.09 (-1.29)
High technology	1.90* (1.72)	1.88* (1.79)	1.91* (1.82)	0.01 (0.63)	-0.24 (-0.23)	0.01 (0.75)	-0.02 (-0.63)	-0.02 (-0.67)	-0.01 (-0.21)	-0.87 (-0.74)	-0.55 (-0.49)	-0.30 (-0.27)
Cash-flow	-0.86*** (-4.45)	-0.86*** (-4.42)	-0.86*** (-4.40)	-0.0003 (-0.27)	-0.09 (-1.2)	-0.0004 (-0.3)	-0.01** (-2.04)	-0.01** (-2.18)	-0.01** (-2.51)	0.09* (1.68)	0.09* (1.79)	0.10* (1.94)
Firm-size	0.62*** (2.86)	0.62*** (2.82)	0.62*** (2.76)	0.001 (0.33)	1.11*** (10.63)	0.001 (0.39)	0.01* (1.88)	0.01** (2.00)	0.01*** (2.59)	0.73*** (10.56)	0.73*** (10.55)	0.73*** (10.61)
Investment-opportunities	0.81*** (3.52)	0.81*** (3.16)	0.81*** (3.47)	0.01* (1.76)	0.63*** (3.27)	0.01** (2.2)	0.003 (0.32)	0.01 (0.94)	0.02* (1.88)	0.46* (1.91)	0.54** (2.26)	0.64*** (2.97)
Constant	-2.79* (-1.81)	-2.75* (-1.78)	-2.80** (-2.00)	0.06** (2.41)	-12.09**	0.06* (1.67)	-0.03 (-0.53)	-0.01 (-0.17)	-0.07 (-0.84)	-1.37 (-0.86)	-2.12 (-1.45)	-2.94**

					* (-7.26)							(-2.36)
Observations	174	174	174	178	178	178	175	175	175	171	171	171
F	13.15***	13.15***	13.15***	22.21***	91.8***	25.39***	7.18***	8.49***	8.56***	89.64***	88.76***	88***
Prob > F	0	0	0	0	0	0	0	0	0	0	0	0
R^2	0.36	0.36	0.36	0.48	0.79	0.51	0.23	0.26	0.26	0.79	0.79	0.79
Jarque-Bera	2.98	2.98	3.02	1.6	2.58	1.95	3.91	4.5	4.55	4.43	4.43	3.84
Prob > □^{2}	0.2258	0.225	0.2214	0.4492	0.2754	0.3768	0.1419	0.1052	0.1025	0.1096	0.1097	0.1539
Breusch-Pagan	1.27	1.55	2.17	0.32	2.48	1.3	1.37	0	0.14	2.61	2.07	1.67
Prob > □^{2}	0.2598	0.2126	0.1403	0.5729	0.1154	0.2547	0.2416	0.9904	0.705	0.1062	0.1498	0.1968

Notes: The dependent variable is investment. GTE, PTE and SE refer to the type of efficiency measures used in each regression. The t-statistics are given in parenthesis. One, two and three asterisks indicate significance levels of 10, 5 and 1 percent respectively.

Table 5 reports the outcomes for the third set of regressions. Again the coefficients associated to the significant efficiency measures are positive. Also most of the technology dummy coefficients are not individually significant. Thus the relevance of technological structure determinants seems weak. Not surprisingly the exceptions occur for the regressions associated to high technology micro firms. The estimated coefficients are positive and significant in all cases. Furthermore, the coefficients associated to the control variables are mostly significant. Thus the results suggest that increases in efficiency, technology, size and investment opportunities may encourage investment.

Statistically, the overall significance tests suggest that all the explanatory variables are necessary for all the regressions. However we should recognize that none of the R^2 values estimated for the third set of regressions is bigger than the ones for of the first set (that use capital-only efficiency measures). These findings seem to confirm that capital-only measures may be adequate explanatory variables of investment decisions. Once more, the Jarque-Bera tests do not reject the null hypothesis of normality and the Breusch-

Pagan tests do not reject the null hypothesis of homoscedasticity. Thus the econometric results seem to support and clarify our previous findings.

We should point out that the previous conclusions can be arguable with basis on the reported results. The number of significant individual coefficients is relatively low in the three regression sets. Indeed it seems plausible that the technical efficiency and technology determinants may be unnecessary. Here we evaluate this hypothesis with joint significance tests. We use the Restricted-Least-Squares technique to assess such hypothesis. On the basis of such tests, we reject the statistical null hypothesis that the determinant coefficients are jointly equal to zero [See Table 6]. Thus the evidence supports that both types of determinants are necessary to explain investment decisions.

Table 6. Analysis of Specification Design
(Omitted Variable Tests)

Omitted variables Estimator	Micro			Small			Medium			Large		
	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE	GTE	PTE	SE
Capital-only measures												
F-test	2.66**	2.06*	2.54**	4.35***	3.81***	3.25**	4.82***	2.25*	1.99*	2.02*	2.37*	7.05***
Labor-only measures												
F-test	3.72***	2.22*	2.50**	3.19**	4.12***	6.15***	4.56***	4.26***	3.46***	2.63**	2.76**	2.71**
Capital-and-labor measures												
F-test	3.70***	3.70***	3.70***	3.47***	3.35**	6.62***	4.31***	2.84**	2.92**	3.90***	4.09***	2.13*

Notes: The table shows the results of the joint significance tests for the three sets of investment-determinant regressions. The unrestricted regressions include de determinant and control variables. The restricted regressions only include the control ones. The determinant variables include the technical efficiency and technology indicators. The control ones include cash flow, firm size and investment opportunities. One, two and three asterisks indicate significance levels of 10, 5 and 1 percent respectively.

Econometrically, one of the main assumptions of the classical linear regression model is that the regression is correctly specified. Here we assess the validity of this assumption with Ramsey´s RESET tests. Such tests are used to detect omitted variable-bias and/or incorrect functional forms. Here we use two variations of such test. The first one, the traditional RESET test, uses powers of the estimated independent variable as regressors. The second one uses powers of the RHS variables. The null hypothesis in both variations is that the regression is adequately specified. We use both RESET tests to assess the specification of each one of the thirty-six regressions estimated. The results are summarized in Table 7.

Table 7. Specification tests for the regression models
(Ramsey´s RESET tests)

	Micro			**Small**			**Medium**			**Large**		
	GTE	**PTE**	**SE**	**GTE**	**PTE**	**SE**	**GTE**	**PTE**	**SE**	**GTE**	**PTE**	**SE**
Capital-only measures												
RESET test	1.01	0.95	0.96	0.5	1.37	2.16*	8.93***	0.96	2.02	1.35	1.07	1.99
Prob > F	0.3888	0.4185	0.4112	0.6832	0.2535	0.0951	0.0000	0.4136	0.1131	0.2602	0.3656	0.1183
RHS-Ramsey test	0.99	1.76*	1.18	1.48	0.92	1.41	1.38	0.68	0.9	0.95	1.07	1.13
Prob > F	0.4653	0.0601	0.3053	0.1386	0.5292	0.1642	0.1811	0.7724	0.5438	0.5006	0.3914	0.3403
Labor-only measures												
RESET test	0.81	0.87	1.7	3.22**	3.44**	2.91**	1.73	6.11***	1.9	1.45	1.25	1.83
Prob > F	0.4911	0.4599	0.1692	0.0242	0.0181	0.0364	0.1627	0.0006	0.131	0.2291	0.2953	0.1429
RHS-Ramsey test	0.55	1.09	0.38	0.99	0.97	1.36	0.15	0.93	0.72	1.72*	1.2	1.14
Prob >	0.8817	0.3705	0.9688	0.461	0.4836	0.1893	0.9996	0.5223	0.7305	0.0667	0.2883	0.3351

F												
Capital-and-labor measures												
RESET test	0.76	1.01	0.72	1.51	2.2*	2.14*	2.93**	4.71***	1.16	1.12	1.25	2.08
Prob > F	0.5171	0.388	0.5392	0.2134	0.0903	0.0975	0.0351	0.0035	0.3268	0.3409	0.2932	0.1045
RHS-Ramsey test	0.99	1.83**	0.78	1.42	1.21	1.3	0.58	0.72	0.43	1.25	1.18	1.34
Prob > F	0.4634	0.0483	0.6707	0.1618	0.278	0.2224	0.857	0.7264	0.9489	0.2551	0.3036	0.2024

The table shows the results of the RESET tests for the three sets of investment-determinant regressions. It shows two versions of such test. The first one, the traditional RESET test, uses powers of the estimated independent variable as regressors. The second one uses powers of the RHS variables. One, two and three asterisks indicate significance levels of 10, 5 and 1 percent respectively.

Table 7 shows that all of the regressions do not have specification errors on the basis of, at least, one RESET test. Thus the evidence suggests that the regressions are adequate to describe the relationships among technical efficiency, technology and investment decisions. Once more the results confirm that capital-only efficiency measures may be useful to explain investment decisions. The regressions that use them measures are better specified than the other ones. Nine out of twelve regressions do not have specification errors on the basis of both Ramsey´s RESET tests. These findings corroborate the relevance of capital as input and of capital-only technical efficiency measures.

We summarize by indicating that the econometric results support the hypothesis that technical efficiency and technology may explain investment decisions. Particularly, they suggest that technical efficiency may encourage investment. However the relevance of technological structure determinants seems weak. The results also show that high-technology manufacturing micro firms invest more than other ones. They also suggest that capital-only technical efficiency measures may be useful determinants of investment decisions. Indeed capital seems a more relevant input than labor. Furthermore, the statistical tests support the convenience of the functional forms used in the regressions.

5. Conclusions and discussion

The issue of how technical efficiency and technology explain investment decisions is not well understood. Here we have shown the results of an econometric investigation regarding the clarification of such issue in the context of the Mexican manufacturing firms. We have used DEA technical efficiency measures, technological structure indicators and OLS regressions to develop the study. We have aimed at clarifying the stylized facts associated with the technical efficiency and technology indicators and at assessing the effects of technical efficiency and technology determinants on investment decisions. We have controlled for the effects of certain of firms´ characteristics.

The assessments suggest the existence of certain stylized facts regarding the technical efficiency-technology relationship. Specifically they suggest that: 1) Capital-and-labor efficiency measures show higher levels of average efficiency than capital-only and labor-only measures; 2) PTE measures show higher levels of efficiency than GTE ones; 3) the most technically efficient firms generally are low-technology ones. Indeed the results show that high-technology firms are the most efficient ones only when the firms are large. Thus; 4) technical efficiency and technology are not necessarily positively correlated. We should point out that these findings are generally robust to the size and type of manufacturing firms.

The econometric results support the hypothesis that technical efficiency and technology may explain investment decisions. Particularly, they suggest that technical efficiency may encourage investment. The results also show that high-technology manufacturing micro firms invest more than other ones. They also suggest that capital-only technical efficiency measures may be useful determinants of investment decisions. Indeed capital seems a more relevant input than labor. Furthermore, the statistical tests support the convenience of the functional forms used in the regression assessments. Moreover they support the necessity to include both types of determinants in the regressions.

We should point out that our findings do no limit themselves to the determination of the significant determinants of investment decisions. Indeed, the evidence shows that relevance of technological structure determinants is weak. Furthermore the results show that the most adequate regressions to explain investment decisions are those that use capital-only efficiency measures. This finding suggests that capital may be a more relevant input than labor.[7] Furthermore, the evidence suggests that increases in firm size and investment

[7] Ito (2010) argues against the use of labor as a measure of technology in the context of Mexican manufacturing industries. Indeed, he mentions that “As a result, we cannot tell if an increase of labour productivity has come from a pure increase of the technology parameter or an increase of the capital stock, or a combination of the two” [Ito (2010:18)]. We should point out that these conclusions arise from the use of a TFP methodology.

opportunities may encourage investments in the Mexican manufacturing firms. The coefficients associated to such control variables are mostly significant and positive.

We conclude by indicating that our study provides elements to understand investment decisions in developing economies. Indeed our results may be useful in the context of the existing debates about the optimal industrial policies for such economies. However, we must recognize that further studies may be necessary to provide policy recommendations. Particularly, we believe that further studies should focus on other microeconomic determinants of investment decisions. Here we have studied technical efficiency and technology ones. Extensions of our analysis may include other determinants like competition ones. The study of these determinants seems a promissory venue for future research.

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