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Testing the effect of firm performance on growth for the Chilean agribusiness

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Abstract

Previous studies of the industrial organization field find that the relationship between firm performance and growth is weak. The objective of this paper is to test this relationship at different quantiles of the firm growth distribution. We also explore the effect of technology gaps and export status on growth. For this, we use Penalized Quantile Regression with Fixed Effects on 420 Chilean agribusiness firms. Key results show that performance, measured as technical efficiency, has a significant and heterogeneous impact on revenue growth. The effect is stronger on slow growing firms: one point increase in technical efficiency increases revenue growth by 1.2 % at the 0.10 quantile, the effect is 0.4 % at the 0.90 quantile. Hence, two key aspects shall be considered in future studies of firm growth and performance: first, to use adequate indicators for performance which capture the entirety of the production process, and second, to consider the non-linearity of their relationship.

Keywords: firm growth, technical efficiency, quantile regression, panel data, fixed effects

JEL codes: L20, D22, C21, C23

1. Introduction

Different theoretical perspectives identify the individual features of fitness, efficiency, or productivity of firms as being determinant on explaining structural change, economic growth, and international trade (Nelson and Winter, 1982; Jovanovic, 1982; Melitz, 2003). Broadly, these theories suggest that these individual features enable firms to outperform their peers and determine their development over time. The economic benefits at the aggregated level arise from the mechanism of reshuffling resources within and between firms. Additionally, there is ample evidence that exposure to international trade speeds up this reallocation process, and thus increases the dynamics in an industry (see the reviews in Rodrik, 1995 and Ciuriak et al., 2014).

Industrial organization studies use diverse measures of firm performance to incorporate it as a determinant for firm growth. The most common measure is financial performance. This surges from the hypothesis that under imperfect capital markets, higher financial performance increases the probability that a firm will survive and also expand operations. Empirical studies have used the firm's market value or Tobin's q ratio as an indicator (Lang and Stulz, 1993; Wernetfelt and Montgomery, 1988), as well as cash flow (Oliveira and Fortunato, 2006; Fagiolo and Luzzi, 2006; Guariglia et al., 2011) and profitability (Coad, 2007; Geroski et al., 1997; Goddard et al., 2002). Recent studies have focused on estimating the effect of labor productivity, as a proxy for firm performance, on firm growth. For instance, Heshmati (2001) analyzes the effect of labor productivity on employment and asset growth of Swedish firms. He finds that the magnitude of the effect is, although statistically significant, negative and rather small: – 0.0001 for both estimations. Gardebroek et al. (2010) find evidence that a 1 % increase in labor productivity barely leads to 0.11 % growth in assets and 0.29 % growth in labor force for dairy processing firms in Europe. Similarly, Bottazzi et al. (2010) measure the effect of labor productivity on sales growth in Italian and French manufacturing firms. They find a statistically significant effect, but the magnitude of the effect is small, i.e.: 0.23 % for the meat and 0.2 % for the dairy sector. Based on the previous results, Bottazzi et al. (2010) conclude that the relationship between firm performance and growth is “actually very weak”.

This study proposes technical efficiency (TE) as an alternative indicator of firm performance. Technical efficiency measures the ratio of observed output to the maximum feasible output from a given set of inputs and a specific technology (Kumbhakar and Lovell, 2000). Thus, TE reveals the performance of individual firms relative to their peers (competitors) in the sector. This is crucial because in the praxis, firms compare their business and practices against their competitors to gain market shares; particularly against those firms operating close to the production frontier or “the best performers”. If a firm is not technically efficient, TE provides a measure of the shortfall of the observed output from the maximum feasible output in the sector and the potential causes for this shortfall (Kumbhakar and Lovell, 2000). When TE is estimated using Stochastic Frontier Analysis (SFA), this shortfall can be decomposed into technical inefficiency and statistical error. We use this approach to estimate TE as a measure for firm performance and hypothesize that it has a positive effect on firm growth.

Differences in the performance of firms also arise from differences in the firms' production environment. Firms within the same industry may face different production opportunities with respect to the settings of the physical, social, or economic environment in which their production occurs (O’Donnell et al., 2008). The conventional measures of technical efficiency do not capture these effects. Battese et al. (2004) and O’Donnell et al. (2008) developed the Metafrontier framework to estimate the technology gaps for producers under different technology sets. This provides a measure of the shortfall between the observed outputs for producers under different technologies relative to the potential output defined by the industry as a whole. Furthermore, it provides a decomposition of this shortfall into group specific technical efficiency and technology gaps. We assume that shortening the technology gaps with respect to the maximum output in the industry would indicate that firms are improving their technology relative to their peers. This may contribute to an increase in output[1], and presumably increased revenue.

Additionally, we consider the effect of export status on revenue growth. Exporters tend to be larger, more productive firms, paying higher wages with more skilled workers than firms only producing for the domestic market (Bernard et al., 2007). These features allow exporters to adjust more rapidly to changing market conditions and cope with intensive competition at the domestic and international level. Moreover, trading in international markets expands the market size in which firms sell their products. This can contribute to an increase in the growth rates of exporters.

[1] Or alternatively, to produce the same output using less input.

Previous studies have focused on determining the effect of the independent variables on the mean of firm growth. However, recent literature has shown that the distribution of firm growth has a leptokurtic shape and heavy-tails, similar to a Laplace distribution, and that this feature holds across most growth indicators (for a review see Coad, 2009). If the firm growth distribution has more observations located at the extreme of the tails than a normal distribution, it seems rather implausible that the covariates have a constant effect over the entire distribution. Furthermore, it is of interest for decision makers to know the effect of firm performance or technology gaps, especially on firms facing negative or low growth rates. In this context, the present study explores whether the effect of the covariates is heterogeneous over the entire distribution of firm growth. To answer this question, we use the Penalized Quantile Regressions with Fixed Effects (PFEQR) for panel data proposed by Koenker (2004), and provide a comparison with the Ordinary Least Square (OLS) and Within Groups (WG) estimations.

We focus our analysis on Chile because it was one of the first Latin American countries to implement a profound process of trade liberalization with an export-oriented strategy. These adjustments combined with its comparative advantage have allowed the agribusiness industry to become the second biggest exporting industry in the country. Nowadays this industry represents 24 % of the Gross Domestic Product (ODEPA, 2011). Furthermore, openness to trade means more competition, higher investment, and productivity growth (Pavcnik, 2002; OECD, 2010). Thus, we expect the agribusiness in Chile to provide the conditions of a very competitive market, where firms are forced to allocate resources efficiently and have low costs to compete for market share. In this study, we center our analysis on the largest sectors within the Chilean agribusiness: meat, fruit & vegetables, dairy, milling, and bakery. These sectors account for 71 % of total agribusiness firms in 2007 and 46 % of the industry revenue (INE, 2007).

This study aims to improve our understating of the empirical relationship between firm performance and firm growth and whether this relationship is constant across the distribution of growth. In this context, we analyze 420 Chilean agribusiness firms over the period 2001 to 2007 by means of the Penalized Quantile Regressions with Fixed Effects (PFEQR) regression.

This paper is organized as follows. Section 2 describes the data and econometric methods. Section 3 presents the results of the estimation and provides a comparison with other approaches. Finally, section 4 summarizes the results and provides the implications of the findings.

2. Methods

To examine the effect of performance and other covariates on firm growth, we use a two-stage estimation. In the first stage, we apply the Metafrontier approach to estimate Technical Efficiency (TE) and the meta-technology ratios (MTR) for each firm. In the second step, we use these estimates to test their effect at different points of the conditional distribution of firm growth using the Penalized Fixed Effects Quantile Regression (PFEQR) proposed by Koenker (2004).

4.2.1 Estimating technical efficiency (TE) and meta-technology ratio (MTR)

This section summarizes the method applied to estimate TE and MTR. We use the Metafrontier model within the Stochastic Frontier Analysis (SFA) developed by Battese et al. (2004) and O'Donnell et al. (2008). This approach provides a framework to estimate the deviations between the observed outputs and the group or sector frontiers, and between the observed outputs and the Metafrontier (or industry frontier) as a single data-generating process.

We define a separate stochastic production frontier for each sector as follows:

$$y_{it} = f(x_{1it}, x_{2it}, \dots x_K \ ; \ \beta^s) * \exp\{v_i^s - u_{it}^s\}, \tag{1}$$

where output y_{it} is the revenue from manufacturing of the i-th firm in the s-th sector at time t; x_K is the k-th input (k= 1,2,…, K) and a dummy variable for exporting firms. The functional form $f(\cdot)$ is specified as a translog function. β^s represents a vector of parameters to be estimated, associated with the s-th sector. The first error term v_i^s is defined as a pure random error independently and identically distributed as $N(0, \sigma_v^2)$ (Aigner et al., 1977). This term captures random events that are not under the control of the producers.

The second error-term u_{it}^s is a systematic and nonnegative random variable for the i-th firm (Schmidt and Sickles, 1984); this error term is used to measure the managerial inefficiency and factors under the firm's control which contribute to the shortfall from the maximum feasible output in the given sector. We assume a half normal distribution for the inefficiency term, $u_i \sim N^+\left(0, \sigma_{u_{it}^s}\right)$, and allow for heteroscedasticity of the inefficiency term by modelling $\sigma_{u_{it}^s} = \exp(z_{ji}\ \rho_j)$ as in Wang and Schmidt (2002). The Z vector comprises the j-th variables, such as the inputs variables and other potential drivers of technical efficiency such as the share of skilled workers, the share of non-productive labor, whether the firm produces for third parties and whether the firm receives fiscal incentives for exporting.

The output oriented measure of TE for any individual i-th firm with respect to the sector frontier is given by:

$$TE_{it}^{s} = \frac{q_{it}}{q_{it}^{m}} = \frac{f(x_{it};\beta^{s})\, e^{(v_{it}-u_{it})}}{f(x_{it};\beta^{s})\, e^{(v_{it}^{s})}} = \exp(-u_{it}^{s}) \in [0,1] \tag{2}$$

TE takes values between zero and one. A firm achieves its maximum feasible output only if TE = 1. If TE < 1, it provides a measure of the shortfall of the observed output to the maximum feasible output in that sector.

The MTR estimation is based on the Metafrontier approach proposed by Battese et al. (2004) and O'Donnell et al. (2008). The Metafrontier is a function that envelops the five sector frontiers: meat, fruit & vegetables, dairy, milling, and bakery. This enables the estimation of the gap between the individual sector frontiers and the Metafrontier, described by the meta-technology ratio (MTR):

$$MTR_{\mathbf{it}} = \frac{e^{x_{it}\beta^{s}}}{e^{x_{it}\beta^{*}}} \tag{3}$$

The MTR is defined as the ratio of output for the i-th firm in the s-th sector relative to the potential output defined by the Metafrontier function (Battese et al., 2004). Thus, the MTR is an index which lies between zero and one and reflects the technology gap with respect to the industry.

4.2.2 Estimating the Penalized Quantile Regression with Fixed Effects (PFEQR)

In this section we describe the method used to test the effect of the covariates, TE, MTR, and export status on firm growth. Classical linear regression methods enable us to estimate the effect of the covariates by changes in the mean of the response variable distribution. These estimations are based on the assumption that the variance of the error term is the same for all combinations of outcomes of the explanatory variables (Wooldridge, 2002). If this assumption is violated, consistent standard errors can be provided by specific econometric techniques. However, for certain specific cases there is an interest in exploring the effect of the covariates on the location and scale parameters of the response distribution. In this context, the quantile regression model proposed by Koenker and Basset (1978) provides a mechanism to estimate the location and scale effect of the covariates across the entire distribution of the dependent variable, without imposing assumptions on their relationship. For instance, if the variance of the error is non-constant, the conditional quantiles will have different intercepts and slopes. If the variance of the error is constant, the conditional quantiles are parallel lines with different intercepts. Thus, this method provides a nuanced analysis of the relationship between the independent and dependent variables. The quantile regression approach has been recently extended for the context of panel data analysis. Koenker (2004) introduces the Penalized Quantile Regression with Fixed Effects (PFEQR) regression, which is employed in the present work.

The model tested in the present study is represented by the following equation:

$$Q_{R \quad g \quad h_{it}}(\tau|x_{it-1}, \alpha_i) = x_{it-1}^{T}\beta(\tau) + T(\tau) + S(\tau) + \alpha_i + u_{it} \tag{4}$$

where τ_j is a quantile in (0,1) and $Q_{R \quad G \quad h_{it}}$ is the conditional quantile of the revenue growth rate from manufactured products for the i-th firm at time t. The term x_{it} is a vector of covariates for the i-th firm at time t-1. These covariates are technical efficiency (TE_{t-1}), the meta-technology ratio (MTR_{t-1}), and a dummy variable for exporting (Exp). The lagged structure of equation (4) implies that previous levels of TE, MTR, and exporting explain the growth rate of revenue in the next time period. In addition, we include a linear time trend (T) and sector (S) dummies to control for time and sector effects; the base group is the meat sector. The $\beta(\tau)$ parameter allows for testing the effect of each covariate in the specified (τ) quantile of revenue growth. The term αi captures unobserved heterogeneity that is time-constant and firm specific; for example, proximity to major markets. We follow Koenker (2004) and assume that these individual effects cause a location shift between the conditional quantiles of revenue. The term u_{it} refers to the idiosyncratic error or time-varying error.

Koenker (2004) proposes to solve equation (4) simultaneously for several quantiles by means of linear programming, as follows:

$$\min_{\beta,\alpha} \sum_{j=1}^{J} \sum_{t=1}^{T} \sum_{i=1}^{N} \omega_j \rho_{\tau,j}\left(y_{it} - x'_{it-1}\beta - \alpha_i\right) + \lambda \quad \sum_{i=1}^{N} |\alpha_i| \tag{5}$$

where $\rho_\tau\ (u) = u(\tau_j - I(u < 0))$ is the quantile loss function, ω_j is the weight given to the *j*-th quantile and λ is the tuning parameter. We follow the standard practice in the quantile regression literature estimating the covariate effects at five quantiles $\tau = \{0.10, 0.25, 0.50, 0.75, 0.90\}$; we weighted the quantiles as $\omega = 1/j$. The standard errors are estimated by bootstrapping with 5,000 replications.

The estimation of the individual effect α_i markedly increases the variability of the estimates. To solve this, Koenker (2004) proposes the use of a penalty term ℓ_1 to reduce the variability of the estimates, and the tuning parameter λ to control the degree of shrinkage. Thus as $\lambda \rightarrow \infty$, the impact of the shrinkage penalty grows and the vector of individual effects shrinks towards zero, also decreasing the variability of the estimates. Nevertheless, the selection of λ remains unclear; λ is arbitrarily chosen. In the next section we explain how we determine the optimal value of the tuning parameter λ for our model.

Under *i.i.d.* error, the coefficients of the PFEQR are vertical shifts of one another with different intercepts. While under non-*i.i.d.* errors, the quantiles exhibit a location and a scale shift. To test this, we use the modified Breusch-Pagan test, which has an asymptotic $\chi 2$ distribution. Its null hypothesis is Ho: $\sigma_i^2 = \sigma^2$. Finally, we also estimate an ordinary least squares regression (OLS) and a Within Groups (WG) regression to compare results. We also test for potential endogeneity of TE_{t-1} and MTR_{t-1} based on the Hausman Test.

4.2.3 K-fold cross validation

By means of the k-fold cross validation, we evaluate the performance of the PFEQR method under different values of λ. This analysis is based on how well the predictions match the observed data for each value of λ, and the value for which we obtain the minimum error.

For this, we split the sample into ten non-overlapping k- or validation-sets. In parallel, we generate ten training sets which contain the remaining k-1 observations. We estimate the model in equation (4) for each training set and obtain the quantile regression coefficients. The preceding coefficients are used to make the predictions and we calculate the weighted sum of absolute residuals (WSR) for each observation in the validation sets. The sum of the WSR for the ten validation sets is the so-called cross validation (CV) error:

$$C = \frac{1}{k}\sum_{i=1}^{k} W \quad (6)$$

We compute the CV error as in equation (6) for values of λ from zero to 500 with intervals of 0.1. Figure 1 presents the results for λ values from 0.1 to 10. We can observe that the CV error decreases as λ increases, and then flattens out. The minimum error is obtained when λ = 2.2, indicated in Figure 1 with a cross. Therefore, we estimate the model using this result.

3. Data

We use data from the 'Annual National Industrial Survey (ENIA)', which was conducted between 2001 and 2007 by the National Institute of Statistics in Chile (INE). The ENIA surveys the full population of manufacturing establishments with 10 or more employees (INE, 2007), based on information provided by the Internal Revenue Service. The data set covers the manufacturing of food products (division 15 of the International Standard Industrial Classification (ISIC)). The divisions are defined by the United Nations (2002) based on similarities in (i) produced goods, (ii) the uses to which the goods are put, and (iii) the inputs, the process, and the technology of production. Finally, firms are classified according to the production activity, which accounts for most of the value added. The data set consists of 2,940 observations. However, the structure of the model with lagged covariates causes the loss of one observation for each firm. Consequently, we lose 420 observations and the analysis is based on 2,520 observations. Table 1 shows the final structure of data set by sector.

Descriptive statistics from the sample are presented in Table 2. Our dependent variable, revenue growth, is derived from the first difference in the logarithm of revenue. Revenue is measured as sales from manufactured products in Chilean Pesos. The values of this variable were deflated and are in constant prices of the year 2007. The mean value for revenue growth rate is 2 % per year. However, its standard deviation is remarkably large, 20 %. The variables T_{t-1} and M_{t-1} were rescaled so that a score of 100 indicates the maximum feasible technical efficiency (T_{t-1}) and meta-technology ratio (M_{t-1}), while zero indicates the minimum. The variable T_{t-1} denotes the individual technical efficiency of each firm relative to its peers within the sector and its mean is 91. The M_{t-1} represents the technology gap between the sectors with respect to the whole industry and has a mean of 75. The dummy variable for exporting is equal to one if the firm exports and it shows that about 10 % of the firms are exporters. However, most exporters operate in the meat, fruit & vegetables, and dairy sectors.

Figure 2 illustrates the quantiles of revenue growth rates. The data shows that firms at the 0.90 quantile of the distribution exhibit an average revenue growth of about 23 %. On the contrary, firms belonging to the 0.10 quantile show negative growth rates of 18 % on average. The average revenue growth at the 0.25, 0.50 and 0.75 quantile is – 6 %, 2 % and 11 %, respectively.

4. Results

In this section, we present the results of the estimation of equation (4) by means of the PFEQR and provide a comparison with the other econometric estimations, OLS and WG.

The estimated coefficients shown in Table 3 reveal substantial differences in the magnitude and significance of the coefficients. The results of the OLS estimation indicate that only T_{t-1} and the dummy for dairy firms have a statistically significant effect on revenue growth. Similarly, the results of the WG estimation suggest that the variable T_{t-1} and the time trend are statistically significant and positive; the latter indicates that firm growth has an upward trend over time. The variable M_{t-1} shows no impact on revenue growth when its effect is measured by either OLS or the WG estimation. The PFEQR estimates reveal that the effect of T_{t-1} on revenue growth ranges from 1.2 to 0.36 %. Furthermore, M_{t-1} shows a significant effect at the 0.10 quantile and at the median of revenue growth. Additionally, exporting has a statistically significant impact at the 0.90 quantile.

The presence of heteroscedasticity in the error term is the primary reason for having differences in the magnitude of coefficient estimates at the different quantiles of the dependent variable. The result of the Breusch-Pagan Test for heteroscedasticity indicates that the variance of the error depends on the values of some of the explanatory variables, $\chi 2$ (1) = 159, *p-value* < 0.001. We also tested for potential endogeneity of TE_{t-1} and MTR_{t-1} by means of the Hausman Test. Endogeneity could arise if there is reverse causality between revenue growth, TE_{t-1} and MTR_{t-1}. However, the Hausman Test fails to find any evidence of endogeneity, F (2, 2511) = 36.96, *p-value* < 0.001.

The results of the PFEQR regression in Table 3 show that time effects are positive and significant for the 0.25, 0.50, and 0.75 quantile of firm growth. This implies that the growth rates have a positive trend over time at those specific quantiles. Furthermore, the dummy variables for the sectors are also significant. Since the base group is the meat sector, the results indicate that, holding constant all other variables, dairy firms have higher growth rates in revenue than meat firms at almost all quantiles (0.10, 0.25, 0.50 and 0.90). Milling firms also show higher changes in revenue at the 0.75 and 0.90 quantiles when compared to meat firms. Meanwhile, bakery firms at the 0.75 quantile grew significantly less than meat firms.

The results also reveal that technical efficiency does not have a homogenous effect on revenue growth. The magnitude of the TE_{t-1} coefficient decreases across the quantiles. The estimated coefficient at the 0.10 quantile indicates that an increase of one point in TE_{t-1}, i.e. from 0.81 to 0.91, increases revenue growth by 1.2 %. At the 0.90 quantile, the marginal effect in revenue growth is 0.4 %. The estimated coefficient at the 0.50 quantile approximates the OLS coefficient.

We investigate whether the coefficients estimated by the PFEQR approach are statistically different than the OLS and WG coefficients. For this, we calculate if the confidence intervals of the OLS and WG estimates contain the PFEQR coefficients. We find that only the coefficient at the 0.50 quantile is not statistically different from the OLS estimate (left-hand panel of Figure 3). Furthermore, the right-hand panel of Figure 3 shows that the WG coefficient differs considerably with the PFEQR estimates, even at the median regression. With the exception of the 0.10 quantile, the PFEQR coefficients are all significantly different from the WG estimate. This result corroborates the fact that the relationship between technical efficiency and growth is non-linear and that firms facing negative revenue growth benefit more from any improvements in technical efficiency.

Additionally, we test for equality of the T_{t-1} coefficients across quantiles using pairwise T-Tests (Table 4). We find that all coefficients are significantly different from each other, except for the 0.75 and 0.90 quantile coefficients. This implies that there is no difference on the effect of T_{t-1} at the 0.75 and 0.90 quantile of the dependent variable; thus, the effect from technical efficiency reaches a lower plateau at the 0.75 quantile and is stable and positive afterwards. This evidence confirms that this relationship is not well explained in an average sense, as the one provided by the OLS estimates. Above all, the results are consistent with the theoretical approaches which predict that production efficiency is a driver for economic growth at the firm level. Furthermore, the results highlight the importance of performance for firms below the industry average, i.e., firms facing low and even negative growth rates.

Therefore, firms which allocate resources efficiently are able to increase revenue at higher rates than their counterparts. Contrary to Heshmati (2001), Bottazzi et al. (2010), and Gardebroek et al. (2010), who find a weak relationship between firm's performance (measured as productivity) and growth, we demonstrate that technical efficiency has a significant and strong effect on revenue growth. The result at the 0.10 quantile confirms the hypothesis that technical efficiency spurs firm revenue in subsequent time periods, particularly when firms face severe low growth rates.

The OLS and WG estimations find no significant effect of MTR_{t-1}. Nevertheless, the PFEQR results reveal that MTR_{t-1} is statistically significant at the 0.10 and 0.50 quantiles of revenue growth. As for the previous variable, the magnitude of the PFEQR coefficient is larger at the lower quantiles of the dependent variable. The results in Table 3 show that at the 0.10 quantile, an increase in MTR_{t-1} of 0.10 raises revenue growth by 0.2 %. At the median, the marginal effect of MTR_{t-1} decreases to 0.07 %. We also find that the PFEQR coefficient at the 0.10 quantile is statistically different than the OLS estimate (left-hand panel Figure 4). The 95 % confidence intervals of the WG estimate contain all quantile coefficients, suggesting that there is no significant difference. Nevertheless, the PFEQR estimates exhibit a narrower confidence interval, which allows the effect of MTR_{t-1} to be measured more accurately.

A T-test indicates that the estimated effect at the 0.10 quantile is statistically different than the one at the median, $\chi 2$ (1) = 4.80, *p-value* < 0.05. This result demonstrates that firms with low revenue growth benefit to a greater extent from the shortening of the technology gap with respect to the whole industry. Improving technological conditions with respect to other firms in the industry make firms more competitive in the market; they can lower product prices and increase market share, increasing revenue at the same time.

The OLS results suggest that the dummy variable for exporting does not have a significant effect on revenue growth. However, the PFEQR estimates point out that exporting has a positive and significant effect at the tail of the distribution. The PFEQR coefficient at the 0.90 quantile lies outside the 95 % confidence interval of the OLS estimate, CI [-1.5; 5.0]. Consequently, the two coefficients are statistically different from one another. The results in Table 3 indicate that those exporting firms at the 0.90 quantile exhibit 6 % higher growth rates in revenue than their counterparts. This might occur because output sold in foreign markets achieves larger volumes, and exporting firms can make a better utilization of the potential of the existing technology and exploit increasing returns to scale.

5. Conclusions

The empirical analysis presented above provides a number of insights into the relationship between firm dynamics and firm performance. First, contrary to the previous literature, we confirm that there is a strong empirical relationship between firm performance and firm growth. Second, this relationship is not homogenous. We prove that the effect is positive and stronger for firms facing low or negative growth rates. The effect of technical efficiency on revenue growth varies from 1.2 to 0.4 % for a one point increase in technical efficiency. These results conform to economic theory because any improvement in managerial efficiency will benefit more firms facing negative revenue growth.

Furthermore, the effect of technology gaps, although smaller in magnitude, is statistically significant at the 0.10 quantile and the median of the conditional distribution of revenue growth. We find that an increase in the meta-technology ratio by one point contributes to a rise in revenue growth by 0.2 to 0.06 %. Considering that the meta-technology ratio average in the sample is 75, there is considerable scope for technological improvements, which will then benefit those firms facing negative growth rates.

The results reveal that technical efficiency and technology gaps better explain the changes in revenue for the lower quantiles. Therefore, managerial ability and technology choice are determinants for improvements in negative growth rates. Meanwhile, large positive growth rates of revenue (higher quantiles) are better explained by market-oriented variables, such as trading to foreign markets. Thus, large increases in revenue are likely to be more affected by market changes than by technological and production choices.

We acknowledge the limitations of this study. We do not provide a detailed decomposition by sector, because the number of observations at the lower and upper quantiles in most sectors is not sufficiently large to produce precise estimates. Dividing the analysis by sector produces large standard errors and imprecise estimates. Nevertheless, the results separated by sectors correspond with the results of the whole industry (see Table A 1 to Table A 5 in the Appendix). Another main constraint is the limited number of explanatory variables used in the regression. This increases the risk of omitted variable bias. This problem originates from the limited number of additional explanatory variables available in the data set. The low R^2 of the OLS regression could be an indication of this problem; nevertheless the pseudo R^2 value for the quantile estimates shows a slight improvement on the fit of the model compared with OLS. Finally, other - more influential - determinants of revenue change, such as input prices, are external factors to this analysis. Thus, future work should consider the effect of allocative efficiency on revenue growth.

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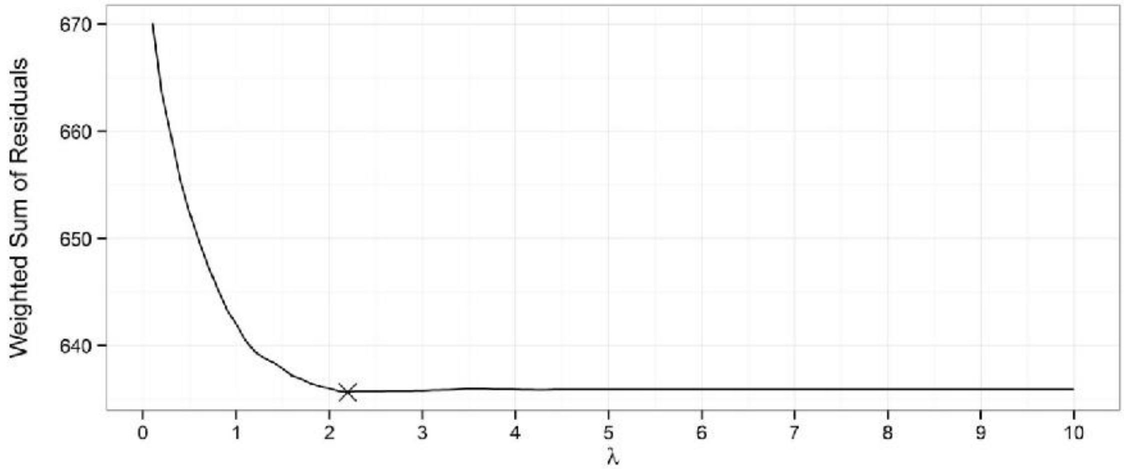
Figure 1 Cross validation error corresponding to λ values.



Source: Author's own calculation

Table 1 Number of observation by sector in the data set.

ISIC Classes	Observations	Firms	Description of the sectors
1511	258	43	Production, processing and preserving of meat and meat products
1513	186	31	Processing and preserving of fruit & vegetables
1520	138	23	Manufacture of dairy products
1531	372	62	Manufacture of grain mill products
1541	1,566	261	Manufacture of bakery products
	2,520	**420**	**Total**

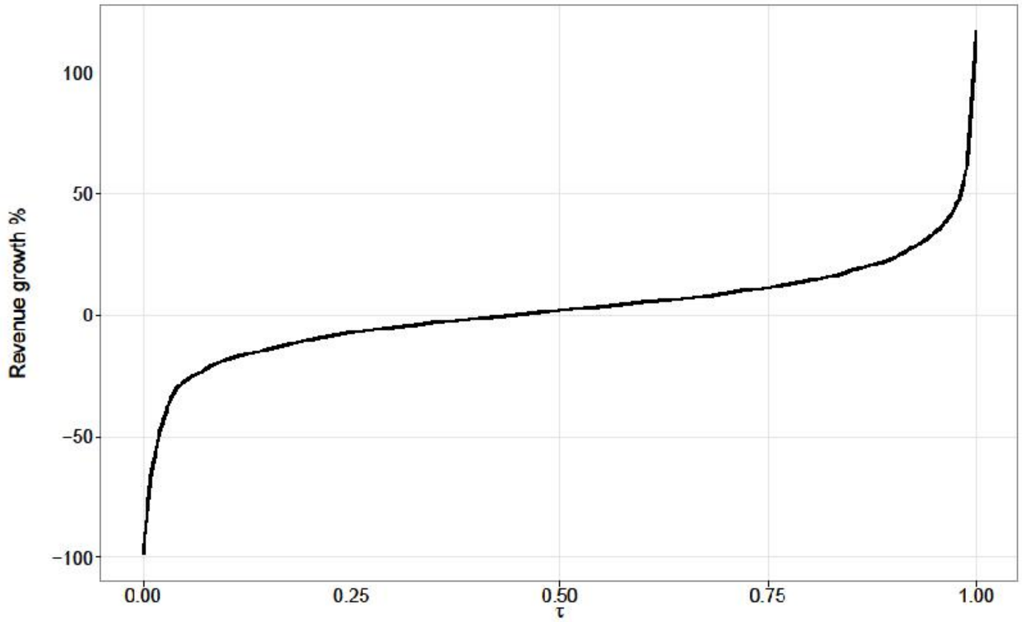
Source: Author's own calculation

Table 2 Description of the variables.

Variables	Mean	Min	Max	Standard Deviation
Revenue (CLP$ 10 Mio.)	426.94	0.65	22,200.00	1,420.00
Revenue Growth	0.02	- 0.98	1.17	0.20
T_{t-1} (0 – 100)	91.06	16.87	99.94	9.89
M_{t-1} (0 – 100)	75.00	12.31	99.99	13.43
Exp (0/1)	0.10	0.00	1.00	0.30
Years	3	1	6	-
Vector of sector dummies				

Source: Author's own calculations

Figure 2 Quantiles of the dependent variable, revenue growth rates.



Source: Author’s own calculations

Table 3 OLS, WG and quantile regression results of revenue growth.

	Pooled OLS	Within Groups	PFEQR				
			τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90
TE_{t-1}	0.0059***	0.0133***	0.0120***	0.0077***	0.0053***	0.0040***	0.0036***
	(0.0007)	(0.0016)	(0.0014)	(0.0010)	(0.0007)	(0.0007)	(0.0008)
MTR_{t-1}	0.0005	0.0008	0.0019***	0.0006	0.0007**	0.0002	- 0.0003
	(0.0003)	(0.0007)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.0006)
Exp_{t-1}	0.0171	0.0290	- 0.0519	0.0078	0.0072	0.0275	0.0623*
	(0.0185)	(0.0372)	(0.0368)	(0.0207)	(0.0166)	(0.0253)	(0.0355)
Trend	0.0030	0.0053**	- 0.0039	0.0053**	0.0048***	0.0083***	0.0022
	(0.0024)	(0.0024)	(0.0044)	(0.0028)	(0.0019)	(0.0019)	(0.0039)
D Fruit & vegetables	0.0357		0.0338	0.0189	0.0282	0.0334	0.0575
	(0.0224)		(0.0480)	(0.0242)	(0.0177)	(0.0242)	(0.0433)
D Dairy	0.0765***		0.0857***	0.0671***	0.0485**	0.0740***	0.0677**
	(0.0207)		(0.029)	(0.017)	(0.020)	(0.028)	(0.034)
D Milling	0.0413**		- 0.0075	- 0.0035	0.0272	0.0780***	0.1419***
	(0.0178)		(0.0298)	(0.0176)	(0.0200)	(0.0197)	(0.0325)
D Bakery	- 0.0203		- 0.0122	- 0.0088	- 0.0190	- 0.0280*	- 0.0263
	(0.0133)		(0.0195)	(0.0123)	(0.0156)	(0.0145)	(0.0245)
Intercept	- 0.5689	- 1.2802**	- 1.3989***	- 0.8460***	- 0.5383***	- 0.3075***	- 0.1108
	(0.0742)	(0.1385)	(0.1657)	(0.1125)	(0.0763)	(0.0777)	(0.0989)
R-squared/ pseudo R†	0.0751	0.1263	0.1059	0.1574	0.1270	0.1272	0.1414

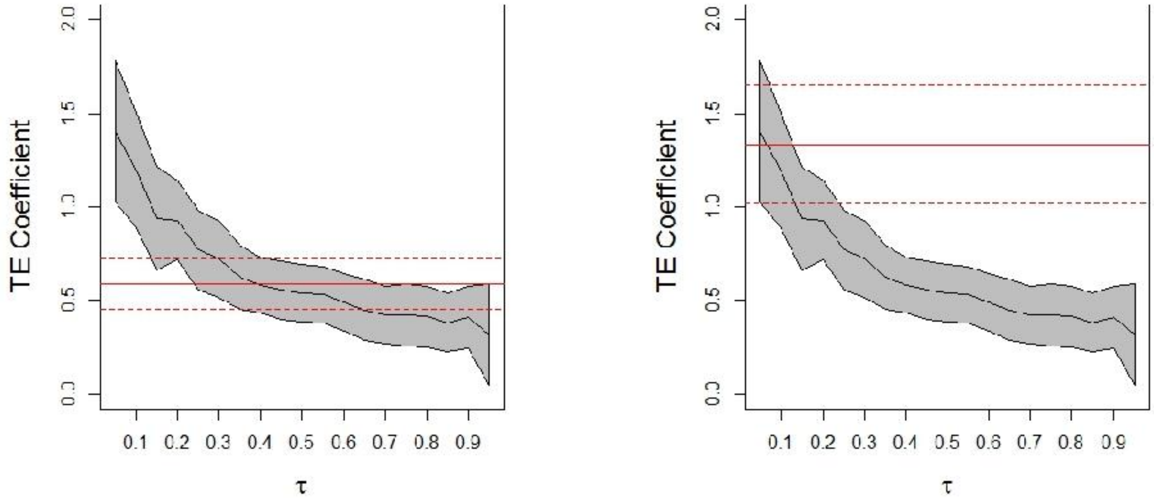
Note: Standard errors in parentheses; significance levels: ∗∗∗/∗∗/∗ denote 0.01, 0.05, and 0.1

Results of the PFEQR estimation were generated using rqpd R code from Bache and Koenker (2011).

†: the pseudo R was calculated as in Koenker and Machado (1999) for quantile regression.

Source: Author’s own calculations

Figure 3 Estimated effect of technical efficiency on revenue growth.



Note: The x-axis represents the quantiles of the dependent variable. The quantile coefficients are depicted with the black solid line and the gray area represents the 95 % confidence interval for the quantile estimates. The red line stands for the OLS coefficients (left) and Within Groups (right), and the dashed lines for their 95 % confidence interval.

Source: Author's own calculations

Table 4 Pairwise T-tests of equivalence of the technical efficient coefficient at the different quantiles.

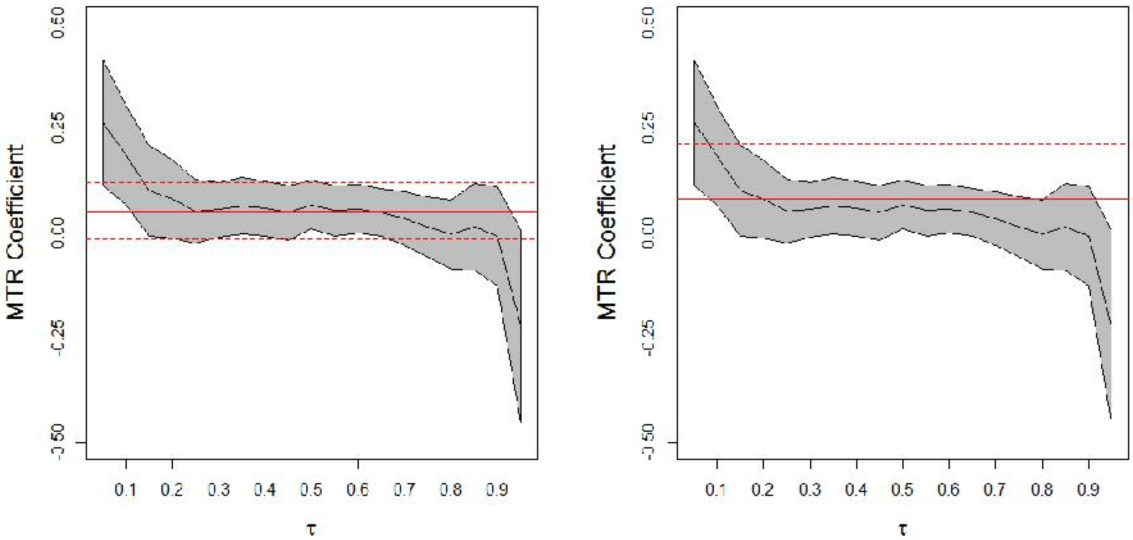
β_T (τ)	**τ = 0.25**	**τ = 0.50**	**τ =0.75**	**τ = 0.90**
τ = 0.10	10.845 ***	19.981 ***	26.911 ***	24.653 ***
	0.001	*0.000*	*0.000*	*0.000*
τ = 0.25		7.570 ***	11.091**	9.247 **
		0.006	*0.029*	*0.002*
τ =0.50			3.828*	3.038 *
			0.051	*0.081*
τ = 0.75				0.284
				0.594

H_0: β_T $(\tau_i) = \beta_T$ (τ_j)

p-value in italics. Critical values χ_1^2 at the 5 % level of significance = 3.84, at 10 % = 2.71

Source: Author's own calculation

Figure 4 Estimated effect of MTR on revenue growth.



Note: The x-axis represents the quantiles of the dependent variable. The quantile coefficients are depicted with the black solid line and the gray area represents the 95 % confidence interval for the quantile estimates. The red line stands for the OLS coefficients (left) and Within Groups (right), and the dashed lines for their 95 % confidence interval.

Source: Author’s own calculations

Appendix

Table A 1 PFEQR estimates for the meat sector.

	PFEQR				
	τ = 0.10	**τ = 0.25**	**τ = 0.50**	**τ = 0.75**	**τ = 0.90**
TE_{t-1}	0.0086***	0.0077***	0.0073***	0.0056*	0.0022
	(0.0034)	(0.0018)	(0.0026)	(0.0033)	(0.0040)
MTR_{t-1}	0.0019	0.0009	0.0000	- 0.0001	0.0001
	(0.0013)	(0.0012)	(0.0011)	(0.0011)	(0.0018)
Exp_{t-1}	- 0.0061	0.0296	0.0274	0.0194	0.0388
	(0.0573)	(0.0355)	(0.0344)	(0.0501)	(0.0634)
Trend	- 0.0037	0.0105	0.0020	- 0.0041	- 0.0136
	(0.0127)	(0.0087)	(0.0091)	(0.0108)	(0.099)
Intercept	- 1.0769***	- 0.9014***	- 0.6704**	- 0.3891	0.0566
	(0.3624)	(0.1946)	(0.2622)	(0.3435)	(0.3925)

Note: Standard errors in parentheses; significance levels: ∗∗∗/∗∗/∗ denote 0.01, 0.05, and 0.1
Results of the PFEQR estimation were generated using rqpd R code (Bache and Koenker, 2011)
Source: Author’s own calculations

Table A 2 PFEQR estimates for the fruit & vegetables sector.

	PFEQR				
	τ = 0.10	**τ = 0.25**	**τ = 0.50**	**τ = 0.75**	**τ = 0.90**
TE_{t-1}	0.1208**	0.0048	0.0030**	0.0008	0.0037
	(0.0061)	(0.0039)	(0.0014)	(0.0020)	(0.0033)
MTR_{t-1}	- 0.0001	0.0015	0.0011	0.0010	0.0021
	(0.0018)	(0.0015)	(0.0008)	(0.0016)	(0.0022)
Exp_{t-1}	- 0.1221	- 0.0621	- 0.0180	0.0321	0.0988
	(0.0844)	(0.0463)	(0.0230)	(0.0598)	(0.0934)
Trend	- 0.0099	- 0.0124	- 0.0033	- 0.0033	- 0.0020
	(0.0204)	(0.0151)	(0.0077)	(0.0131)	(0.0241)
Intercept	- 1.1381*	- 0.5085	- 0.2866**	- 0.0011	- 0.2512
	(0.5980)	(0.3189)	(0.1142)	(0.1933)	(0.3434)

Note: Standard errors in parentheses; significance levels: ∗∗∗/∗∗/∗ denote 0.01, 0.05, and 0.1
Results of the PFEQR estimation were generated using rqpd R code (Bache and Koenker, 2011)
Source: Author's own calculations

Table A 3 PFEQR estimates for the dairy sector.

	PFEQR				
	τ = 0.10	**τ = 0.25**	**τ = 0.50**	**τ = 0.75**	**τ = 0.90**
TE_{t-1}	0.0047	0.0044*	0.0022	0.0027**	0.0027
	(0.0029)	(0.0023)	(0.0018)	(0.0013)	(0.0033)
MTR_{t-1}	0.0017	0.0012	0.0016	0.00010	0.0009
	(0.0014)	(0.0010)	(0.0012)	(0.0014)	(0.0018)
Exp_{t-1}	0.0607	0.0281	-0.0074	0.1274*	0.0855
	(0.0579)	(0.0459)	(0.0712)	(0.0673)	(0.1029)
Trend	0.0197	0.0129	0.0164*	0.0152	0.0067
	(0.0200)	(0.0087)	(0.0083)	(0.0120)	(0.0205)
Intercept	- 0.7284**	- 0.5656**	- 0.3274*	- 0.2332	- 0.0553
	(0.3301)	(0.2347)	(0.1925)	(0.1659)	(0.3821)

Note: Standard errors in parentheses; significance levels: ∗∗∗/∗∗/∗ denote 0.01, 0.05, and 0.1
Results of the PFEQR estimation were generated using rqpd R code (Bache and Koenker, 2011)
Source: Author's own calculations

Table A 4 PFEQR estimates for the grain sector.

	PFEQR				
	τ = 0.10	**τ = 0.25**	**τ = 0.50**	**τ = 0.75**	**τ = 0.90**
TE_{t-1}	0.0098 (0.0015)	0.0097 (0.0015)	0.0057 (0.0021)	0.0040 (0.0014)	0.0003 (0.0024)
MTR_{t-1}	- 0.0005 (0.0018)	- 0.0004 (0.0013)	0.0008 (0.0013)	- 0.0002 (0.0010)	- 0.0044 (0.0018)
Exp_{t-1}	0.0287 (0.0784)	0.0424 (0.0523)	0.0149 (0.0536)	- 0.0689 (0.0432)	- 0.0216 (0.0845)
Trend	-0.0337 (0.0141)	- 0.0069 (0.0104)	0.0210 (0.0111)	0.0289 (0.0074)	0.0253 (0.0084)
Intercept	- 0.8741*** (0.1839)	- 0.9059 (0.1504)	- 0.6278 (0.1586)	- 0.2746 (0.1552)	0.5320 (0.2451)

Note: Standard errors in parentheses; significance levels: ∗∗∗/∗∗/∗ denote 0.01, 0.05, and 0.1
Results of the PFEQR estimation were generated using rqpd R code (Bache and Koenker, 2011)
Source: Author’s own calculations

Table A 5 PFEQR estimates for the bakery sector.

	PFEQR				
	τ = 0.10	**τ = 0.25**	**τ = 0.50**	**τ = 0.75**	**τ = 0.90**
TE_{t-1}	0.153*** (0.0021)	0.0114*** (0.0020)	0.0078*** (0.0013)	0.0068*** (0.0013)	0.0063** (0.0022)
MTR_{t-1}	0.0029*** (0.0009)	0.0011** (0.0005)	0.0007* (0.0004)	0.0002 (0.0005)	- 0.0002 (0.0010)
Exp_{t-1}	- 0.0371 (0.0636)	- 0.0026 (0.0332)	- 0.0393 (0.0462)	- 0.0479 (0.0576)	0.0843 (0.1208)
Trend	- 0.0039 (0.0048)	0.0049 (0.0035)	0.0051** (0.0020)	0.0053*** (0.0020)	- 0.0002 (0.0045)
Intercept	- 1.7981*** (0.2269)	- 1.2394*** (0.2069)	- 0.7897*** (0.1368)	- 0.5873*** (0.1421)	-0.3907 (0.2381)

Note: Standard errors in parentheses; significance levels: ∗∗∗/∗∗/∗ denote 0.01, 0.05, and 0.1
Results of the PFEQR estimation were generated using rqpd R code (Bache and Koenker, 2011)
Source: Author’s own calculations