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Call for Research Proposals
Competition and Market Power in Latin America and the Caribbean
A Research Network Project
RG-K1198

Productivity and Market Power: The Case of Manufacturing firms of Peru 2002-2019

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ABSTRACT

This proposal analyzes the impact of price-cost markup (PCM) on the rate of growth of total factor productivity (TFP) for formal companies in Peru in the period 2002-2019 obtained from the National Business Survey (INEI-ENE 2023). In contrast to the vast empirical literature on the subject, the research method of the project uses, on the one hand, estimated of firms' PCM & TFP based upon methodologies provided by new empirical industrial organization literature (e.g., De Locker & Scott 2022, De Locker & Warzynski 2012, and De Locker 2011, 2011a). On the other hand, uses a non-experimental design with specific 'Causal Machine Learning' techniques developed by Belloni, Chernozhukov, and Hansen (2014a, b) and Chernozhukov, Chetverikov, Demirer, Duflo, Hansen, Newey, and Robins (2018, 2017) to find causal relationships of firms' PCM on rate of change of TFP. These techniques essentially reduce the biases of omission of covariates and variables 'confounding' and 'overfitting' of the estimates of the parameter associate to firms' market power represented by PCM estimates. The project's research methods will provide new insights into the relationship between PCM and TFP growth in Peru. The findings will be valuable for policymakers and businesses interested in understanding how to promote economic growth.

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1. BACKGROUND AND LITERATURE REVIEW

As many advanced economies (IMF 2019, De Loecker & Eeckhout 2021), firms' market power and concentration seem to be risen in Latin America and Caribbean countries with negative economic and political effects at the macro level and in some specific sectors (Eslava, Melendez, Urdaneta 2021; UNDP 2021 a, b; Hordones &. Zoratto 2021; Ji & Yépez-García 2017; and Tello 2022). However, the estimations of market power and concentration and their impacts on countries and firms' performance have followed the structure-conduct-performance industrial organization (SCPIO) paradigm, highly criticized, and rejected by IO experts (e.g., Berry, Gaynor, Scott 2019, Bresnahan 1988 and Schmalensee 1989).

In contrast to the ad-hoc SCT specifications and estimations, the IO experts' alternative approach of the market analysis (originated by Bresnahan 1988 and Schmalensee 1989) called the new empirical IO (NEIO) is based upon methods for understanding firm conduct and markets on the basis of the relevant economic primitives: demand, cost, and pricing conduct. Thus, under the assumptions that firms maximize profits and must cover their total costs, the equilibrium price (and other outcomes) will be determined by demand, marginal costs, and fixed (possibly sunk) costs, along with the conditions of competition that shapes the pricing behavior (Berry *et al* 2019).

Surprisingly, Angrist & Pischke (2010) do not give merit to what they call the *Credibility Revolution in Empirical Economics of Industrial Disorganization* which impose a superstructure of assumptions for market analysis which should be of concern. Instead, they advocate for better research designs and simple and transparent empirical methods of direct causal analysis that trace a shorter route from facts to findings (e.g., the work of Hastings 2004 or the work of Hausman and Leonard's 2002 who combine both approaches, the causal and the NEIO). These criticisms are well understood by De Loecker & Scott (2022). In a positive note these authors suggest that for the case of market power estimations combining the NEIO demand and production approaches may assist researchers in selecting assumptions and evaluating structural models. On the other hand, although Angrist & Pischke (2010) find that empirical results generated by a good research design more compelling than the conclusions derived from a good theory, they hope to see industrial organization move towards stronger and more transparent identification strategies in a structural framework.

Given these approaches to analyze markets, this project combines the causality and the NEIO approaches to estimate, on the one hand, market power and firms' total factor productivity -TFP- and, on other hand, to evaluate the impact of market power on the rate of total factor productivity growth of manufacturing firms of Peru for period 2002-2019. Subject to the statistical results, the proposal ultimate goal is not only to find any causal relationship between market power and firms' total factor productivity but also to provide some guidelines of competition industrial policies.

2. RESEARCH QUESTIONS AND OBJECTIVES

Studies of Tello & Tello-Trillo (2023), Tello (2023) and Alcorta (2011) finds that firms' price-cost margins -PCM_{it}- estimations have increased in period 1998-2019[1]. Furthermore, the Pearson correlation coefficients between firms estimates of PCM and TFP (levels and the rate of change) are positive and statistically significant for all firms' size and market orientation.[2] Given these figures, the general objective of the project is to investigate the causal relationship between PCM[3] and productivity for a sample of formal enterprises of the manufacturing sector of Peru, period 2002-2019. The specific questions or objectives that arise from the general objective are:

i) Estimate firms' $PCMs_{it}$ using the production approach described in De Loecker & Scott (2022), De Loecker &. Warzynski (2012), De Loecker, J. (2011) and references therein[4].

ii) Estimate firms' total factor productivity index $lnITFP_{it}$ using firms production data and De Locker (2011a) method.

iii) To analyze the causal relationships of firms' price-cost margins on the rate of change of total factor productivity base upon causal machine learning techniques[5] (i.e., DML 'double debiased' method[6]).

3. METHODOLOGY

Figure A2 of the Annex Tables sketch the three aspects of the methodology of the project. The first aspect is associated to the structure-conduct-performance industrial organization (SCTIO) paradigm. Peruvian literature studies of this paradigm (e.g., Tello 2012, Tello & Tello-Trillo 2023, y Alarco 2011) have found that there is a negative impact of external (import) competition on the price-cost

[1] The sample for period 1998-2008 was 10000 firms of all sectors (see Alarco 2011). For period 2002-2019 the average sample of firms was 401 per year of the manufacturing sector (see Tello 2023).

[2] Table A1 from Annex Tables and Figures.

[3] Price-cost margins, price-cost markups and Lerner Index are used as measures of market power (e.g., Syverson 2019, Verboven 2012).

[4] Subject of the availability of the data of INEI-ENAHO (2023), the project would estimate the firms' PCM_{it} using the demand approach described in De Loecker & Scott (2022) and references therein.

[5] Machine learning is a branch of artificial intelligence (AI) and computer science that focuses on using data and algorithms to mimic the way humans learn, gradually improving their accuracy. IBM points out to Samuel (1959) as the one who coined the term "machine learning." Machine learning is an important component of the growing field of data science. Using statistical methods, algorithms are trained to make classifications or predictions, uncovering key information within data mining projects. (https://www.ibm.com/cloud/learn/machine-learning). On the other hand, AI is a branch of computer science that deals with building intelligent machines capable of performing tasks that normally require human intelligence. At https://builtin.com/artificial-intelligence.

[6] Described in Chernozhukov, Chetverikov, Duflo, Hansen, Newey and. Robins (2017, 2018).

margins (PCM) of formal companies of Peru, although such impact is not robust statistically. However, the impact of external competition is negative when the degree of participation of firms in the market increases. On the other hand, decrease in output tariffs reduces Peruvian firms' productivity growth for non-exporters while increasing productivity growth for exporters. In contrast, a reduction in input tariffs increases productivity for all firms. Finally, the studies have found increases of firms' PCM of different sectors in period 1998-2019. In period 2012-2019, firms' PCM in manufactures, however, have remained relatively constant.[7]

The second aspect is associated to the new empirical industrial organization (NEIO) paradigm. Based upon the production approach of the NEIO described in De Locker & Scott (2022), De Locker & Warzynski 2012, and De Locker (2011), the project will estimate measures of formal manufacturing enterprises' market power (through PCM_{it} estimations) and the total factor productivity ($ITFP_{it}$) based on the Economic Annual Survey provided by INEI-EEA 2023 for period 2002-2019.[8] The three keys steps of this methodology are:

First: Measure of Firm Market Power (μ_{it}^{V}) depends upon Revenues (R_{it}^{V}), Costs (C_{it}^{V}) and output elasticity (Q_{it}) with respect and input V_{it}[9] (θ_{it}^{V}).

[1] $\mu_{it}^{V} = \theta_{it}^{V}.(R_{it}^{V}/C_{it}^{V})$; i=1..$N_t; t = 2002 - 2019;$

Second: Estimations of the Production Function to estimate θ_{it}^{V}. Production functions estimations follows the methodologies of Olley & Pakes (1996), Levinsohn &. Petrin (2003), Ackerberg, Caves, & Frazer (2015) or De Loecker (2011a).[10] From this step, the firm $ITFP_{it}$ is estimated.[11]

Third: Estimation of firm mark-up (μ_{it}) as an average of markups of the variable inputs of the production function.[12]

The third aspect of the methodology is associated to the causal methodology suggested by Angrist & Pischke (2010). The techniques used are the Causal Machine Learning (MLC) methods[13], specifically the DML method. This methodology is based upon of the following ad-hoc SCPIO specification:

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[7] See Figure A1 of the Annex Tables and Figures.
[8] The questionnaires of the survey for 2019 it is found in:
https://drive.google.com/drive/folders/1u2kUrBqF_723aYFUH-ZtftT7hThVGSI7?usp=drive_link
[9] Potential variables inputs could be materials and labor.
[10] Details in Tello (2023) and De Locker & Scott (2022).
[11] Details in Tello (2023).
[12] See formula [19] in De Locker & Scott (2022).
[13] According to Baiardi & Naghi (2020), these techniques i) are data use tools to recover complex interactions between variables and flexibly estimate the relationship between the outcome, the treatment indicator and the covariates; ii) allow the inclusion of a large number of covariates, even when the sample size is small, and the use of regularized regressions; iii) allows a systematic model selection to be implemented; and iv) they are very useful when the interest is in estimating the effects of heterogeneous treatments.

[2] $dlnITFP_{it} = \beta.\mu_{it} + \vec{X}_{it}'.\overrightarrow{\delta} + \varepsilon_{it}; i = 1, \ldots N_t; t = 2012 - 2019$

This specification relates firms' market power (μ_{it}) and other factors or control variables ($\vec{X}_{it}$) that determines the rate of change of firms' total factor productivity ($dlnITFP_{it}$).[14] Apart from potential endogeneity problem due to μ_{it}, specification [2] still has the problems of confounding variables and overfitting. To reduce the statistical implications of these problems, the Double/debiased machine learning' or DML proposed by Belloni, Chernozhukov, and Hansen (2014a, b), Chernozhukov, Chetverikov, Demirer, Duflo, Hansen, Newey, and Robins (2018, 2017) and Baiardi A., A. Naghi (2020) is used. The stages of this method is based upon following specifications:

[3] $dlnITFP_{it} = \beta.\mu_{it} + go(\vec{X}_{it}) + U_{it}; i = 1, \ldots N_t; t = 2002 - 2019$

[4] $\mu_{it} = mo\left(\vec{X}_{it}\right) + V_{it};$

The stages are the following:

First. the 'debiased' ML estimators are obtained using Machine Learning, ML, tools (for example LASSO[15]) of both equations and the errors $\widehat{U}_{it}$ and $\widehat{V}_{it}$ of [3] and [4] are estimated.

Second: The estimation of $\hat{\beta}$ is obtained from the regression of $\widehat{U}_{it}$ on $\widehat{V}_{it}$. To obtain more robust estimators, the whole sample could be divided in pairs of samples. In one of them, called the 'auxiliary' sample group, the first stage of the DML method is applied. The second sample called 'main' is used to compute $\widehat{U}_{it}$ and $\widehat{V}_{it}$ with the estimations of the 'auxiliary' sample. With these errors estimated using the 'main' sample, the parameter of interest $\hat{\beta}$ is obtained from the regression of $\widehat{U}_{it}$ on $\widehat{V}_{it}$. A more robust $\hat{\beta}$ is obtained from the average of the estimators $\hat{\beta}$ of each pair of samples.[16] The DML also can be applied with instrumental variables of μ_{it}[17] previous applications of standard exogeneity tests.[18]

Finally, according with the results found, the proposal expects to arrive to some policy suggestions on industrial (market) policies consistent with the results and hopes to point out ways to improve the structure of models of the NEIO style using the idea of Hendren and associates (2020).[19]

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[14] According to Syverson (2011) factors that affect firms' productivity could be trade liberalization (or import competition), firms productive features such as firm' size, capital-labor ratio, market orientation, foreign ownership assets, etc.

[15] Ahrens, Hansen, Schaffer (2019) y Códigos PDLASSO (2023).

[16] Note that this methodology can be applied for different estimations of market power and productivity.

[17] See Berry (2022) and Bartik (1991) for potential instruments of μ_{it}.

[18] Details in Haussman (1978), Wu (1974), Wooldrige (1995), Stock and Yogo (2005) and Lee, McCrary, Moreira, Porter (2022).

[19] See Figure A1 of the Annex of Tables and figures.

4. DATA DESCRIPTION

The main source of data is the Peruvian Economic Annual Survey (Encuesta Económica Anual in Spanish) of manufacturing enterprises provided by INEI-EEA (2023) for the period 2000-2019. The questionaries of the EEA[20] include most of the data needed to implement the methodology described in the previous section. The Peruvian studies quoted in this proposal are examples of research using such data source.

5. SCHEDULE

No	Activity Description	Number of Months
1	**10.20.23** Project Begins. Selected research proposals.	0
2	**11.30.23** Progress report of the research paper to the IDB. (Report includes a preliminary literature review, methodology, basic facts, and a plan of the results).	1
3	**12.12.23** Virtual discussion seminar of the project via Zoom to discuss and refine the selected proposals and methodology to be used in the research paper.	0.5
4	**04.15-30.24** i) First draft of research papers and delivery to the IDB of complementary support documents utilized in the research paper. ii) Second virtual discussion seminar of the project via Zoom to discuss the first draft of the research papers. Date to be determined.	4.5
5	**08.26.24** Final version of research papers, and delivery to the IDB of any further versions of the datasets utilized in the research paper.	4
	Total	10

[20] https://drive.google.com/drive/folders/1u2kUrBqF_723aYFUH-ZtftT7hThVGSI7?usp=drive_link
This link provides the questionnaires for 2019.

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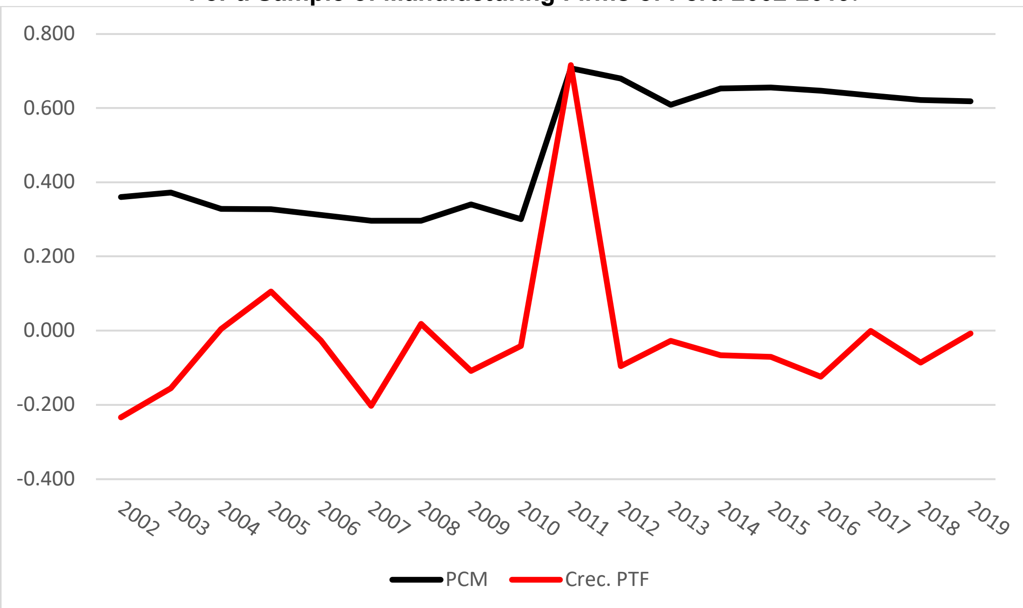
ANNEX TABLES AND FIGURES

Figure A1
Averages Price-Margin Cost (PCM) and Anual Rate of Total Factor Productivity (%TFP) For a Sample of Manufacturing Firms of Peru 2002-2019.



Fuente: INEI-EEA (2023), Tello (2023). Author's elaboration. Unbalanced Panel of 7214 observations. PCM= (Real Output Value- Real Value of Inputs & Real Wages)/(Real Output Value), by firm 'i' at year 't'. Anual Rate of Total Factor Productivity, also by firm 'i' at period t is obtained from the De Locker (2011a) method estimated by Tello (2023). The values of both variables in the Figure A1 are the sample averages per year of each variable. Outlies firms with PCM values greater than one were dropped out from the averages.

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Table A1
Pearson Correlation Coefficients Between PCM and TFP (level and rate of growth) 2002-2019.

Sample Description	$lnITFP_{it} - lnITFP_{i(t-1)}$	$ITFP_{it}$
$L_{it} \leq 20, DX_{it} = 1$	0.344***	0.608***
$20 < L_{it} \leq 99, DX_{it} = 1$	0.261***	0.608***
$L_{it} \geq 100, DX_{it} = 1$	0.318***	0.576***
$L_{it} \leq 20, DX_{it} = 0$	0.314***	0.609***
$20 < L_{it} \leq 99, DX_{it} = 0$	0.247***	0.640***
$L_{it} \geq 100, DX_{it} = 0$	0.232***	0.636***

Fuente: INEI-EEA (2023). Tello & Tello-Trillo (2023). Author's elaboration. For each firm 'i' at period 't', L_{it}, is the number of total workers of the firm; $DX_{it} = 1$ means an export firm, $DX_{it} = 0$ means a non-export firms. The average number of firms per year is 401. $ITFP_{it}$ is the index of total factor productivity of a firm. *** level of significance lower than 1%.

Figure A2

Research Methodology