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The Case of Manufacturing Firms of Peru 2002-2019

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Abstract*

This paper uses seven standard market power indicators (price-cost margin, and six drawn upon the production approach) to estimate the effect market power on the rate of change of total factor productivity for a sample of formal manufacturing firms of Peru for the period 2002-2019. After applying exogeneity tests and implementing panel data with fixed effects instrumental variable method, the results are not clear about the causal relationship between market power and firms' TFP. However, when the Double-Debiased machine learning (DML) causal method is applied for fixed effects panel data with and without instruments, firms' market power robustly seems not to affect their respective total factor productivity regardless of the market power indicators and instruments used. The paper also presents four examples which are consistent with this causal result suggesting that the relationship between market power and productivity needs to be analyzed on a case-by-case basis considering the product development of sectors, the influence and activities of firms and economic groups in the domestic economy and foreign markets, and the level of development of the country's productive structure.

JEL classifications: D24, L1, L6

Keywords: Market power, Total factor productivity, Causal machine learning

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1. Introduction

As in many advanced economies (IMF, 2019; De Loecker & Eeckhout, 2021), firms' market power¹ and concentration has 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). Estimations of market power and concentration and their impacts on countries and firms' performance in developing countries, have usually followed the structure-conduct-performance industrial organization (SCPIO) paradigm, which has been highly criticized and rejected by IO experts (e.g., Berry, Gaynor, & Scott, 2019; Bresnahan, 1989; and Schmalensee, 1989). In contrast, the alternative approach of market power analysis (originated by Bresnahan, 1989, and Schmalensee, 1989), called the new empirical IO (NEIO), is based upon methods for understanding firm behavior on 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).

Angrist & Pischke (2010), however, argue that the NEIO imposes a superstructure of assumptions for market analysis which should be of concern. Rather, 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, 2002, who combine both causal and NEIO approaches). They find that empirical results generated by a good research design are more compelling than the conclusions derived from a good theory.

This study takes the NEIO approach to estimate formal manufacturing firms' market power of a middle income Latin American country, Peru, and the Angrist & Pischke (2010) empirical approach to examine the causal relationship between the rate of growth of firms' total factor

¹ According with OECD (2021), market power or mark-up is defined as the extent to which price exceeds marginal cost (or an approximation of marginal cost) is a performance measure of the degree of competition in a market or industry, so in this paper we use degree of competition, mark-up, and market power indistinctly.

productivity, TFP, and market power measure through different types of markups found in the literature for a sample of formal firms of manufactures of Peru.

The paper is organized into four sections. Section 2 presents a brief literature review, including the estimation of productivity and firms' market power indicators. Section 3 presents the analysis of the endogeneity problem, and Section 4 presents the estimations and results of a sample of Peruvian manufacturing firms using the Double-Debiased machine learning (DML) methodology for the period 2002-2019. Finally, Section 5 summarizes the main findings.

2. Literature Review

In the last 30 years, the recent literature on the relationship between firms' market power and productivity is based on both the SCPIO and NEIO approaches. Theoretically, however, the relation is not clear. Thus, Battisti, Marvasi, Jona-Lasinio and Sopranzetti (2021) warn us that, although the association between markups and productivity is of primary importance in economics, theoretical considerations show that the relation between these variables is non-trivial and causality can go in either direction, implying that the issue is mainly empirical. On the other hand, Syverson (2011) postulates three mechanisms by which competition (lower market power) may increase or decrease productivity. The first is a selection mechanism by which competition moves market share toward more efficient (i.e., lower-cost and generally therefore lower-price) producers, shrinking relatively high-cost firms, sometimes forcing their exit, and opening room for more efficient producers. The second mechanism acts through efficiency increases within plants or firms. Heightened competition induces firms to take costly productivity-raising actions that they may not otherwise. The third, but negative mechanism of competition, is the Schumpeterian caveat. Vives (2007) points out, under certain conditions, a higher level of competition can diminish a firm's incentives to make productivity-enhancing investments. Aghion, Bloom, Blundell, Griffith, & Howitt (2005), based upon a theoretical model, complement these mixtures of mechanisms and postulate an inverted U relationship between market power and firms' total factor productivity. Specifically, they postulate that firms with similar technological levels, lower markups reduce pre-innovation rents (increase incremental profits from innovating), which may lead to R&D investments, and higher TFP, to escape competition; *this is the escape*

competition effect. In contrast, product market regulation will affect post-innovation rents when innovation is predominantly generated by laggard firms with low initial profits. This reduces the research intensity of laggard firms—or reduces the rents from followers who innovate to catch up to rivals and increase TFP. This is the *Schumpeterian effect*. The combination of these two effects explains the inverted-U relationship between competition and growth. When the escape competition effect dominates the Schumpeterian effect, the relation between market power and TFP is negative, and when the second effect dominates the first the relation between both measures is positive.

The summary of the literature described in Table A1 of the annex is consistent with the mixture and opposite results of the relationship of market power and firms TFP. In general, the estimations results depend on the measures of firms' TFP and markups, the degree of competition or market, the type of country (developed and developing country) and industry, and the period of analysis.

Thus, the studies of Rivera-Padilla (2023), Battiatì, Marvasi, Jona-Lasinio, and Sopranzetti (2021), and Nadiri & Nandi (1999) find a positive correlation between firms' markups and TFP. Contrarily, the studies of Dai, Li, & Cai (2018), Holmes & Schmitz (2010), and Bloch & Kan Tang (2007) find a negative relationship between those two indicators. Unclear correlations between firms' market power and TFP have also been found in the studies of Steinbrunner (2023) and Kiyota (2010).² A key aspect of the unclear correlation between firms' market power and TFP found in the NEIO literature associated to the production approach is the measure or the indicators of firms' markups, market power or the degree of competition.³ Thus, Flynn, Gandhi, and Traina (2019) show that standard methods to estimate production functions do not identify markups. This nonidentification creates spurious skewness in estimated markup distributions. They solve this identification problem using an ex-ante structure on the returns to scale solves the identification problem. In their application for US public firm data and in a Monte Carlo experiment, they find that applying constant returns to scale performs remarkably well and reduces the skewness in the markup distribution among public firms by as much as half in comparison to nonidentified

² It should be notice that the studies reported in Table A1 is a small sample of the extensive literature on the subject.

³ Other approaches to measure market power may be found in OECD (2021), White (2013), and Baker & Bresnahan (1992) among many others.

estimates. Van Heuvelen, Bettendorf, & Meijerink (2021), on the other hand, show that extending the flexible input incorrectly with fixed contract hours results in an increasing markup. They propose a flexible input temporary labor, and its output elasticity results from estimating a structural value-added production function. Alternatively, a gross output function and materials as flexible input are combined.

Raval (2023a) has recently shown, based upon manufacturing datasets from Chile, Colombia, India, Indonesia, the United States, and Southern Europe, as well as store-level data from a major U.S. retailer, that markups estimated using labor and materials do not have the same distribution. Furthermore, markups estimated using labor are negatively correlated with markups estimated using materials; moreover, they exhibit greater dispersion and have opposite time trends. He argues that non-neutral productivity differences across firms can explain these findings. In a follow-up paper, Raval (2023b) develops a flexible cost share estimator to account for firms' production function heterogeneity when estimating the output elasticity. This estimator generates markups that are similar when estimated with different inputs.

The next section takes up this relationship by estimating firms' TFP and market power indicators for a sample of manufacturing firms of Peru for the period 2002-2019 and thereafter estimating the causal relationship between both.

3. Estimation of Firms' Productivity and Market Power Indicators

Firms' TFP is estimated using the De Loecker (2011)⁴ and Tello (2024a) method. In the case of a Cobb-Douglas production function, PF, the specification is:

$$[2.1] \quad \ln r_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \tau tr_{it} + \sum_s \beta_s q_{st} + a_{it}^* + \varepsilon'_{it} ;$$

where:

i=firm, t=time, s=sector,

$\tilde{r}$: Logarithm de la real production value

l : Logarithm of labor

m : Logarithm of real value of materials of inputs

⁴ Details in Table A2.

k : Logarithm of real value of capital

tr : Average of preferential tariffs

q_{st} : Real output value of sector s

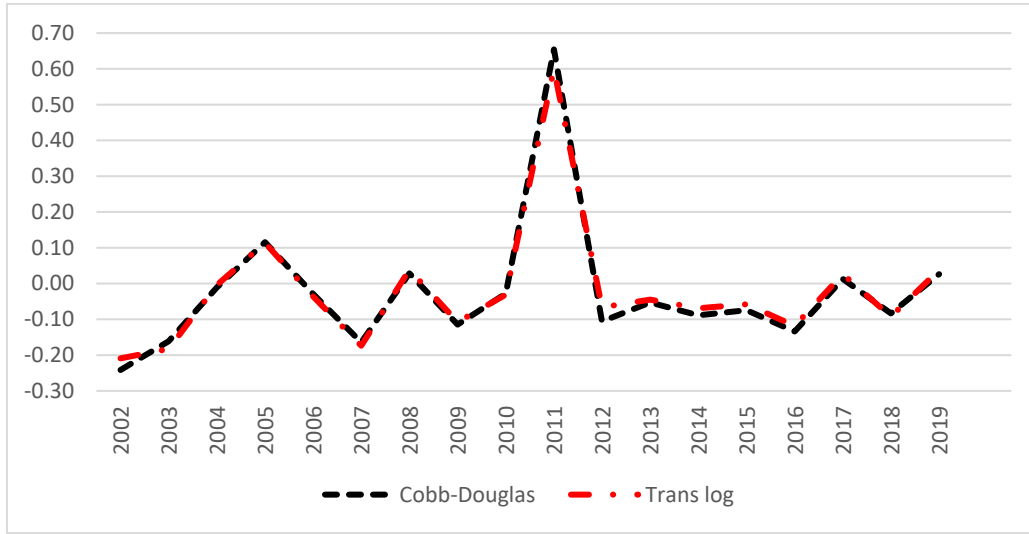
The data come from INEI-EEA (2024) for the period 2002-2019. ε'^*_{it} captures idiosyncratic output and demand shocks, and a^*_{it} is the logarithm of firm TFP.

Figure 1 shows the annual average firms' rate of change of TFP for the period using trans log and Cobb-Douglas production functions. The behavior of both TFP is similar, with a peak in 2011 and slightly raising toward 2019.

Seven indicators of firms' market power are then computed. The first is the price margin ratio (pcm), and the second and third one is the labor and input market power indicators developed De Loecker & Scott (2022), De Loecker & Warzynski (2012), and De Loecker (2011).⁵ The last two indicators are the labor and input materials of Raval (2023b). Except for the pcm and Raval's indicators all the remaining indicators use both TFP PF estimators, derived from the trans log and Cobb-Douglas PF. Consequently, there are seven firm market power indicators. Figures 2 and 3 and Table 1 show the evolution and values of the annual average of each market power indicator.

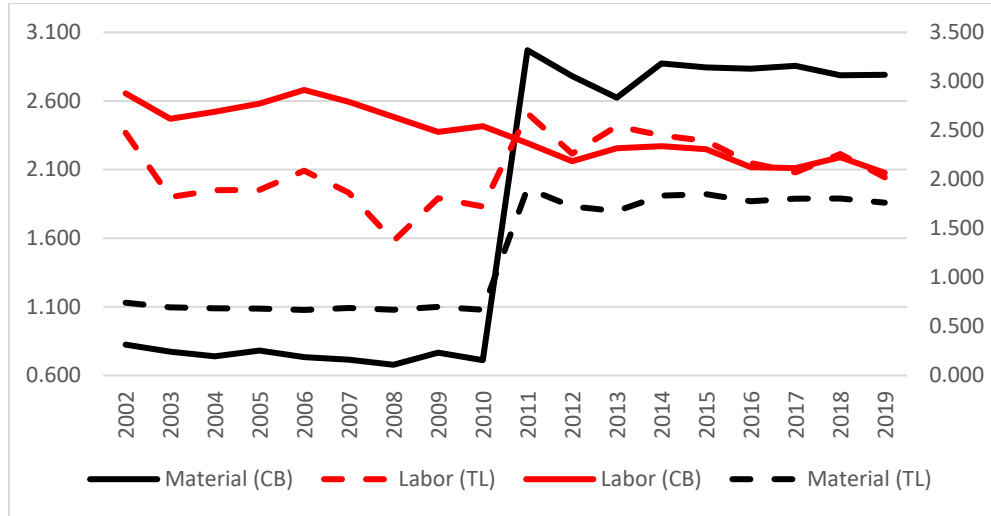
⁵ Table A2 of the Annex presents the key formulas, and the econometric methods used for the market power indicators.

Figure 1. Annual Trend in Growth of Firms' Productivity $\Delta \ln TFP_{it}$



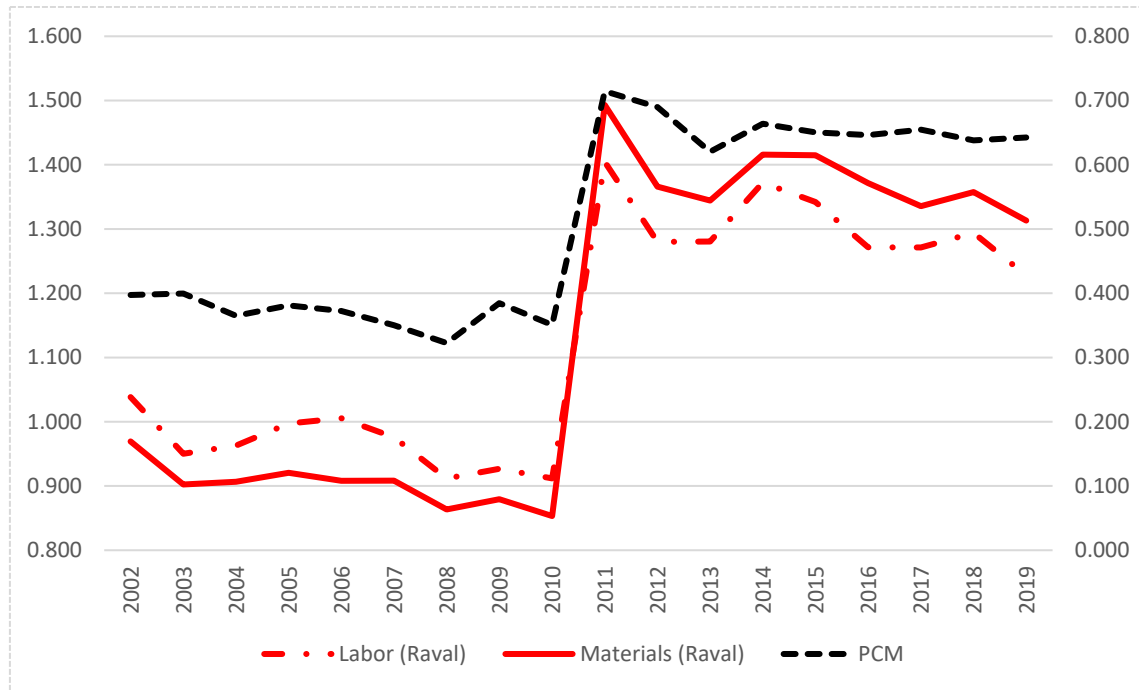
Source: Authors' formulation based on INEI-EEA (2024). The outlier in the year 2011 was caused by a change in the composition of cost share in INEI's sample. Details below. CB= Cobb-Douglas. TL= Trans log.

Figure 2. Annual Trend in Market Power Using De Loecker's Estimation



Source: Authors' formulation based on INEI-EEA (2024). The outlier in the year 2011 was caused by a change in the composition of cost share in INEI's sample. Details below. CB= Cobb-Douglas. TL= Trans log.

Figure 3. Annual Trend in Market Power, Other Indicators



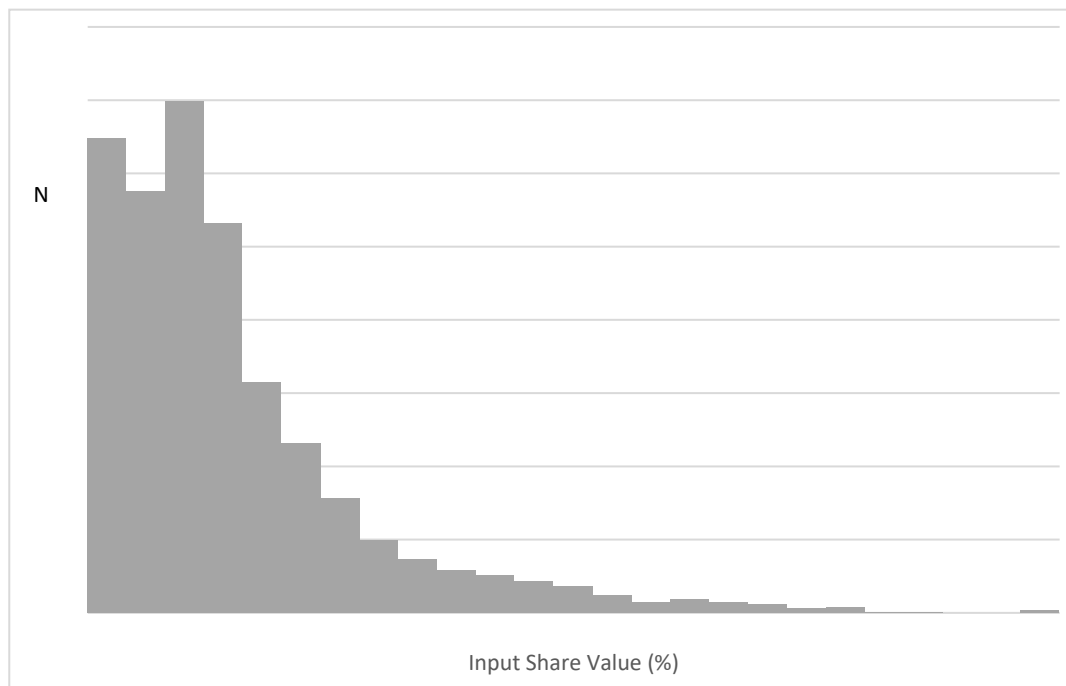
Source: Authors' formulation based on INEI-EEA (2024). The outlier in the year 2011 was caused by a change in the composition of cost share in INEI's sample. Details below.

Table 1. Annual Average of Firms' Market Power Indicators (μ_{vit}) and Instrumental Variables											
Year	pcm_{it}	Cobb Douglas PF		Trans log PF		μl_{2it}	μinp_{2it}	RSI_{it}	RSI_{it-1}	MS_{it}	MS_{it-1}
		μl_{1it}	μinp_{1it}	μl_{1it}	μinp_{1it}						
2002	0.397	2.878	0.824	2.368	0.742	1.038	0.969	0.167	0.177	0.009	0.009
2003	0.400	2.617	0.773	1.899	0.695	0.950	0.902	0.170	0.165	0.010	0.010
2004	0.365	2.690	0.739	1.950	0.684	0.963	0.907	0.181	0.164	0.011	0.010
2005	0.381	2.772	0.781	1.952	0.681	0.997	0.921	0.220	0.209	0.012	0.012
2006	0.372	2.912	0.734	2.092	0.668	1.005	0.908	0.199	0.192	0.009	0.010
2007	0.350	2.792	0.715	1.931	0.689	0.976	0.908	0.175	0.169	0.009	0.009
2008	0.323	2.638	0.678	1.579	0.669	0.912	0.863	0.183	0.180	0.010	0.010
2009	0.385	2.484	0.767	1.891	0.699	0.927	0.880	0.195	0.209	0.007	0.007
2010	0.351	2.543	0.711	1.831	0.671	0.912	0.853	0.190	0.189	0.007	0.007
2011	0.714	2.369	2.970	2.510	1.907	1.404	1.493	0.216	0.197	0.008	0.007
2012	0.690	2.185	2.782	2.216	1.723	1.280	1.366	0.237	0.234	0.009	0.009
2013	0.620	2.317	2.624	2.417	1.677	1.281	1.344	0.264	0.261	0.007	0.007
2014	0.664	2.339	2.874	2.349	1.835	1.372	1.416	0.282	0.274	0.009	0.008
2015	0.650	2.308	2.844	2.309	1.848	1.342	1.415	0.314	0.303	0.009	0.009
2016	0.646	2.125	2.835	2.148	1.777	1.272	1.371	0.314	0.325	0.009	0.010
2017	0.655	2.115	2.856	2.079	1.804	1.271	1.336	0.325	0.318	0.010	0.010
2018	0.638	2.226	2.787	2.214	1.805	1.294	1.358	0.321	0.337	0.010	0.010
2019	0.642	2.067	2.791	2.043	1.763	1.225	1.308	0.323	0.305	0.013	0.012
Average	0.543	2.408	1.998	2.131	1.356	1.168	1.188	0.250	0.247	0.009	0.009
Annual Ave.	0.514	2.465	1.783	2.099	1.241	1.135	1.140	0.238	0.234	0.009	0.009
$\hat{\rho}$		-0.296***		0.177***		0.738***					

Source: Author's calculations based on INEI-EEA (2024), De Locker & Warzynski (2012), and Raval (2023b), Table A2. The final sample before regression is 5,643 for Cobb Douglas PF and 5,641 for Trans log PF. μ_{1vit} De Locker and associates market power indicators. μ_{2vit} Raval (2023b) market power indicators.

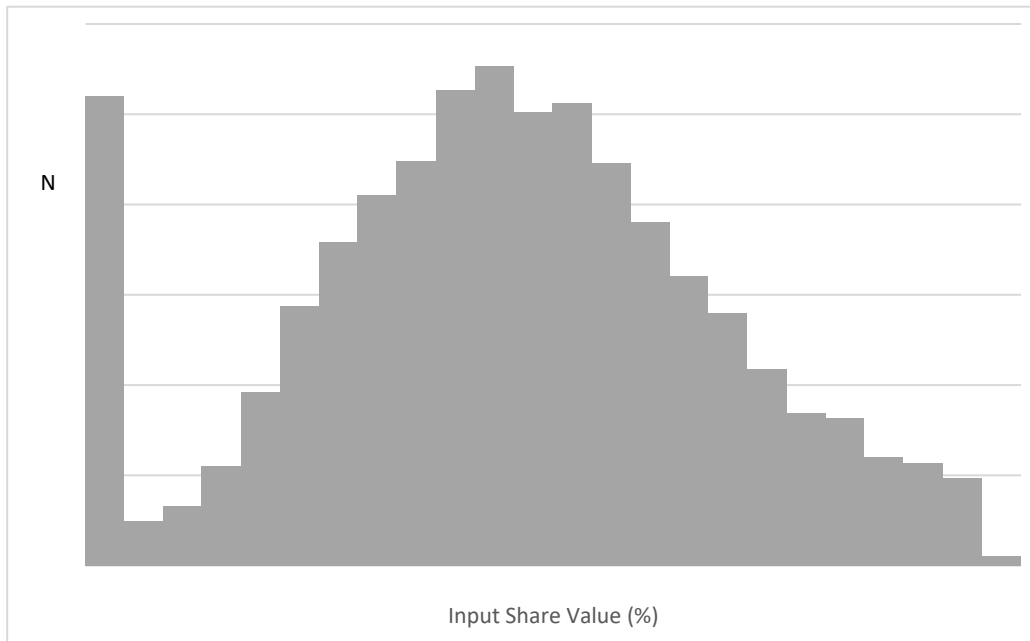
These figures and tables indicate that except for the labor market power indicator of De Locker and associates, all the indicators follow the same behavior, as firms' estimated TFP peaked in 2011. Before and after 2011 such indicators either decreased or were constant. Figures 4 and 5 show the reason for the 2011 peak of these indicators.

Figure 4. Input Share Values, 2012-2019



Source: INEI-EEA (2024). Distribution of the materials input shares between values [0;1]. The Y-axis is the number of observations N, (firms per year) and X-axis is the input share values in percentages.

Figure 5. Input Share Values, 2002-2010



Source: INEI-EEA (2024). Distribution of the materials input shares between values [0;1]. The Y-axis is the number of observations, N, (firms per year) and X-axis is the input share values in percentages.

The average value of the input share of firms' sample for periods before and after 2011 were respectively 0.50 and 0.18. In 2011, the INEI-EEA (2024) modified the composition of the enterprises data. According to the technical data sheets, from 2000 to 2011 the interviews were made with a sample probability of 1 per firm. From 2011 onwards the data included an expansion, factor, changing how they recollect information. Consequently, as Figures 4 and 5 indicate, the average input share and their firms' distribution changed.⁶ These changes implied the peak of most market power indicators and of firms' TFP.

⁶ Before and after 2011 the annual average labor cost share of firms was 0.17 and 0.20, respectively. These figures explain the decreasing evolution of labor market power indicator of De Loecker et al.

3. Endogeneity Problems of the Relationship between Firms' Productivity and Market Power

The specification for estimating firms' TFP is the following:

$$[3.1] \quad \Delta \ln TFP_{it} = \delta \cdot mp_{it} + \vec{X}'_{it} \cdot \vec{\beta} + \alpha_i + \varepsilon_{it}; i = 1..N_t; t = 2002 \dots 2019$$

where for each firm i at period t , $\Delta \ln TFP_{it}$ is the rate of change of TFP, mp_{it} is the variable of interest, an indicator of market power, $\vec{X}_{it}$ is the vector of control variables, α_i is a firm individual effect and ε_{it} is the standard stochastic error. Specification [1] is based on an extensive literature surveyed by Bartelsman & Doms (2000), Isaksson (2007), Syverson (2011), and Thuy Linh (2021), among many others. Apart from the variables of interest, mp_{it} ,⁷ the control variables are well diversified, as firms' size, propensity to exports, trade policy, capital-labor ratio, and foreign-owned firms are those most used in the literature.⁸ Due to limited availability of information, Table 2 lists only the mean and standard deviations of the interest and control variables considered here.

⁷ There are many indicators that have been used in the literature instead of mp_{it} , among others: concentration ratios, Herfindahl and Lerner indices, price cost margin, and firms market shares.

⁸ Other variables are R&D, learning by doing, innovation, and age (e.g., Castiglionesi & Ornaghi, 2011; IMF, 2016; and Gonçalves & Martins, 2016); management experience, internet connection, and access to finance (e.g., Raihan, Nafiz & Nur, 2017; Camino-Mogro & Bermúdez-Barrezueta, 2021a; and Camino-Mogro, 2021b); and human capital (e.g., Danska-Borsiak, 2018).

Table 2. Indicators of the Specification of Firms' Total Factor Productivity

No	Variable	Description	Mean	S.D.
1. Dependent Variable				
	$Index(lnTFP_{it})$	Index of Logarithm of the total factor productivity of companies, calculated from De Loecker (2012) methodology directly as $lnTFP_{it} - mean(lnTFP_{it})$	0.01	0.76
	$\Delta lnTFP_{it}$	Differential logarithm of the total factor productivity of companies $Index(lnTFP_{it})$	-0.03	0.54
2. Variables of Interest				
Cobb-Douglas	pcm_{it}	Ratio of a firm Output value - input and labor cost over output value	0.54	0.22
	μ_{1it}	Mark-up calculated from De Loecker (2012) methodology for labor component.	2.41	1.28
	$\mu_{inp_{1it}}$	Mark-up calculated from De Loecker (2012) methodology for material component.	2.00	1.44
	μ_{2it}	Mark-up calculated from De Loecker (2012), adjusted by Raval (2022), methodology for labor component.	1.17	0.45
	$\mu_{inp_{2it}}$	Mark-up calculated from De Loecker (2012), adjusted by Raval (2022), methodology for material component.	1.19	0.48
Trans log	μ_{1it}	Mark-up calculated from De Loecker (2012) methodology for labor component.	2.13	1.13
	$\mu_{inp_{1it}}$	Mark-up calculated from De Loecker (2012) methodology for material component.	1.36	0.74
	μ_{2it}	Mark-up calculated from De Loecker (2012), adjusted by Raval (2022), methodology for labor component.	1.17	0.45
	$\mu_{inp_{2it}}$	Mark-up calculated from De Loecker (2012), adjusted by Raval (2022), methodology for material component.	1.19	0.48
3. Variables of Control				
	$\Delta lnGDP_t$	Differential of the logarithm of national GDP, real soles.	0.05	0.02
	TI_t	Terms of trade (Base 2007 = 100)	92.07	13.70
	$tr_pref_output_{it}$	Weighted average of preferential rates, by CIIU.	4.42	5.03
	$tr_pref_input_{it}$	Weighted average of preferential rates for intermediate or capital goods products, by CIIU.	3.87	4.52
	$tr_pref_out_DX_{it}$	Weighted average of preferential rates * exporter	1.31	2.15
	$tr_pref_inp_DX_{it}$	Weighted average of preferential rates for intermediate or capital goods products * exporter	1.13	1.96
	$post_{it}$	Dummy variable that indicates whether the year is 2010 or later for each company	0.67	0.47
	$post_ln_Import_{it}$	Logarithm of imports from 2010 onwards	11.60	8.30
	ln_Import_{it}	Logarithm of imports by CIIU	16.93	1.69
	$ln_KL_ratio_{it}$	Logarithm of the firm's capital-labor ratio	10.53	1.01
	$Ratio_KM_{it}$	Percentage share of imported capital by CIIU	0.24	0.37

No	Variable	Description	Mean	S.D.
	DX_{it}	Dummy variable that indicates if the company is an exporter	0.44	0.50
	DFO_{it}	Dummy variable that indicates if more than 50% of the firm's capital is foreign	0.19	0.39
	$DL1_{it}$	Dummy variable that indicates if the company is large (more than 100 workers)	0.60	0.49
	$DL2_{it}$	Dummy variable that indicates if the company is large (between 20 and 100 workers)	0.32	0.47

Source: Authors' compilation based on INEI-EEA (2024).

As suggested by the theoretical and empirical literature firms market power may be affected by changes of TFP and therefore may create an endogeneity problem in specifications that determine firms TFP. This section offers five tests are applied to identify the relevance of four instrumental variables,⁹ the Residual Supply Index (RSI), firm market share, and their respective one lag variable.¹⁰ The first test is the Wu (1974)-Hausman (1978) exogeneity test. The other four tests involve the relevance of the instrument (i.e., the Stock & Yogo 2005, and Montiel & Pflueger, 2013, tests), the relevance of the market power indicator in the second stage of the IV method regardless of the selected instrumental variable (i.e., the Andrew & Rubin AR test), or a for a determined selected instrument (i.e., the Lee, McCrary, Moreira, Porter test).

The results of these tests, which are shown in Tables 3-6 for all the selected instrumental variables, are the following:

1. Most of the exogeneity tests do not reject the null hypothesis of exogeneity. However as suggested by Bellemare (2015) (based upon Wooldridge 2015) “*a failure to reject the null of exogeneity in a Hausman test is not a blank check to “accept” exogeneity.*” The problem of accepting exogeneity is that the sign and statistical significance of some the estimated coefficients of the standard

⁹ Other instruments have been also used with a mixture of results of the effects of market power on firms' productivity. It should be noted, that regardless of the sign and the statistical relevance of those effects, still the causality relationship between firms' market power and their TFP remains to be analyzed.

¹⁰ *RSI* defined as the ratio of net real output value of a manufactured sector (discounted the sample firms of that sector) over the total real output value of the sector. Details in Ji & Yépez-García (2017).

panel data estimation are different of those of the corresponding IV panel data estimation.¹¹

2. Despite of the high correlation coefficients between the instruments (particularly with *RSI*) and the market power indicators,¹² the two tests with null of hypothesis of weak instruments are not robust for most of the market power indicators.
3. Similarly, the two tests wherein the null hypothesis is the weak parameter of the second stage of IV method are not robust across the market power indicators and instruments.

While these results are not entirely clear, there is the additional problem of causality, which is addressed in the next section.

¹¹ See Tables A5 to A9.

¹² Table A4.

Table 3. Statistical Tests of Instrumental Variables (RSI_{it})

Variables	Cobb Douglas PF					Tran slog PF				
	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵
pcm	55.87*	58.66*	-2.09**	2.99*	0.152	56.14*	58.96*	1.88*	2.20	0.30
μlp_{1it}	5.67	5.95	-0.60	2.37	2.206	2.01	2.11	0.01	0.05	1.37
μinp_{1it}	97.23*	102.08*	2.10**	2.69	1.241	103.39*	108.57*	1.90*	2.00	1.01
μlp_{2it}	16.41*	17.23	1.29	2.00	4.238	16.79*	17.63	1.22	1.59	3.81
μinp_{2it}	11.48	12.06	1.04	2.04	3.502	10.36	10.88	0.96	1.57	3.02

Source: Authors' calculations based on INEI-EEA (2024). 1 Ho: Weak Instrument. 2 Ho: Weak instruments in linear instrumental variables regression that is robust to heteroscedasticity, autocorrelation, and clustering. 3 Ho: Weak IV parameter (with corrected standard errors). 4 Ho: Weak IV parameter with any Instrument. 5 Ho: variable of interest is exogenous. (Wu-Haussman test). *** represents significance <0.01; ** < 0.05 and * < 0.1.

Table 4. Statistical Tests of Instrumental Variables (RSI_{it-1})

Variables	Cobb Douglas PF					Tran slog PF				
	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵
pcm	35.77*	37.56*	-0.63	1.26	7.139	35.88*	37.68*	-0.74	1.57	7.518
μlp_{1it}	4.28	4.49	0.07	1.24	0.839	1.83	1.92	-0.01	0.09	0.498
μinp_{1it}	66.96*	70.30*	-0.72	1.47	2.699	72.42*	76.04*	-0.87	1.87	2.930
μlp_{2it}	15.66	16.44	0.31	1.37	0.307	15.90	16.70	-0.63	1.71	0.442
μinp_{2it}	6.69	7.02	0.32	1.21	0.475	6.01	6.32	-0.33	1.42	0.634

Source: Authors' calculations based on INEI-EEA (2024). *** represents significance <0.01; ** < 0.05 and * < 0.1.

Table 5. Statistical Tests of Instrumental Variables (*Market Share_{it}*)

	Cobb Douglas PF					Tran slog PF				
Variables	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵
pcm	162.14*	170.23*	8.55***	71.90***	19.19	170.11*	178.63*	8.98***	79.30***	23.82
μlp_{1it}	3.24	3.40	-0.02	3.77*	3.11	42.19*	44.31*	-0.05	30.73***	27.07*
μinp_{1it}	0.54	0.57	0.01	0.63	0.54	0.52	0.54	-0.01	0.45	0.52
μlp_{2it}	12.93	13.57	-2.15	12.02***	10.93	12.20	12.82	-2.06**	11.70***	10.60
μinp_{2it}	6.47	6.79	-0.02	6.18**	5.95	10.42	10.94	-0.03	9.62***	9.25

Source: Authors' calculations based on INEI-EEA (2024). *** represents significance <0.01; ** < 0.05 and * < 0.1.

Table 6. Statistical Tests of Instrumental Variables (*Market Share_{it-1}*)

	Cobb Douglas PF					Tran slog PF				
Variables	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵	Stock & Yogo F-Test (2005) ¹	Montiel & Pflueger (2013) ²	t-F Test de Lee <i>et al</i> (2022) ³	AR test (1949) ⁴	Exogeneity test ⁵
pcm	34.04*	35.74*	-3.04***	20.46***	29.04**	34.32*	36.04*	-3.06***	20.78***	29.26**
μlp_{1it}	8.67	9.10	1.44	8.35***	8.17	25.34*	26.61*	2.68***	21.44***	21.45
μinp_{1it}	0.10	0.11	0.00	0.13	0.10	1.33	1.40	0.01	1.25	1.32
μlp_{2it}	7.84	8.23	1.30	7.75***	7.42	8.31	8.73	1.39	8.16***	7.85
μinp_{2it}	11.24	11.80	1.85	10.40***	10.36	9.31	9.78	1.58	8.75***	8.72

Source: Authors' calculations based on INEI-EEA (2024). *** represents significance <0.01; ** < 0.05 and * < 0.1

4. The Machine Learning Causal Relationship between Firms' Productivity and Market Power

Apart from the endogeneity problem, equation [3.1] above is subject to two additional problems, which are the existence of confounding variables and the difficulty of determining the optimal number of control variables to avoid “overfitting.” The Pool or Panel data estimator of [3.1] does not address these two problems. The Double Debiased Machine Learning method, DML, deals with these problems. The DML belongs to techniques of causal methodologies and was developed by Belloni, Chernozhukov, and Hansen (2014a, b) and Chernozhukov, Chetverikov, Demirer, Duflo, Hansen, Newey, and Robins (2018, 2017). Applied to specification [3.1] and according to Ahrens, Hansen, Schaffer, Wiemann (2023), the DML method can be intuitively understood using the following equations:

$$[4.1] \quad \Delta \ln TFP_{it} = \delta \cdot mp_{it} + go(\vec{X}_{it}) + U_{it}; i = 1, \dots, N; t = 2002 - 2019$$

$$[4.2] \quad mp_{it} = mo(\vec{X}_{it}) + V_{it};$$

Under the assumptions of $E[Cov(U, mp/X)] = 0$ and $Var(mp/X) \neq 0$, and defining $E(\Delta \ln TFP/X) = \delta \cdot mp_{it} + go(\vec{X}_{it})$ and $E(mp/X) = mo(\vec{X}_{it})$ then, regardless of the estimation method of [4.1] and [4.2], the estimated coefficient of the causal effect $\hat{\delta}$ of mp on $\Delta \ln TFP$ can be estimated by regressing $\hat{U} = \hat{\delta} \cdot \hat{V}$.¹³ The machine learning methods¹⁴ make it possible to reduce the potential bias originating from the confounding variables and overfitting problems. On the one hand, the nonlinear functions $mo(\vec{X}_{it})$ and $go(\vec{X}_{it})$ of [4.1] and [4.2] may incorporate a large number of control variables which may overcome the number of observations;¹⁵ in such cases machine learning methods reduce the number of these variables, avoiding the overfitting. On the other hand, the reduction of the bias of confounding variables may be addressed by introducing

¹³ This regression is based upon the Frisch–Waugh–Lovell (FWL) theorem (Frisch & Waugh, 1933; Lovell, 1963 and 2008).

¹⁴ Such as Lasso, random forest, support vector machines, ridge regression and so on (<https://www.geeksforgeeks.org/machine-learning-algorithms/#types-of-machine-learning-algorithms>), are designed and optimized for predicting the outcome in a test sample (details in Baiardi & Naghi, 2020).

¹⁵ Even when the number of raw covariates is relatively small, the inclusion of technical controls (e.g., dummy variables for geographical location, time periods, etc.), interactions and transformations can lead to settings in which the number of covariates is large relative to the sample size.

potential confounding variables through $go(\vec{X}_{it})$ in [4.1] and the orthogonal estimated error of [4.2], which may eliminate the correlations between the interest variable, mp , and the potential confounding variables incorporated through $mo(\vec{X}_{it})$. The DML method has been extended to IV methods (e.g., Ahrens, Hansen, Schaffer, Wiemann 2023) and panel data.¹⁶

The fixed effects panel data DML with and without instrumental variables estimations follow the next stages: First the whole sample is divided in $K=2, 5$ groups. Second, for any pair of these sample groups, two different regressions are estimated (using the Lasso ML technique) for each pair of sample groups. One of them called the auxiliary group, the ML regression coefficients of equations [4.1] and [4.2] are estimated. The other pair called the main group is used to estimate the errors of those equations which are used to obtain the estimated parameter of the regression of $\hat{U}_{it}$ on $\hat{V}_{it}$. Third, a robust $\hat{\delta}$ is obtained by computing the average of the estimators $\hat{\delta}$ of each pair of the sample groups. In all these steps, i) the list of control variables is shown in Table 2 (above), ii) $go(\vec{X}_{it})$ and $mo(\vec{X}_{it})$ are quadratic polynomial functions of the control variables, and iii) the instrumental variables are those of Table 1.

Tables 7-11 show the statistical results for both sets of groups of the fixed effects panel data estimations, with and without instruments using the DML approach. The figures of all these tables suggest that, regardless of the market power indicators and instruments used, firms' market power does not cause changes in their firms' TFP. This result is consistent with the lack of a robust evidence of such a relationship found in all the exogeneity tests of the previous section.

¹⁶ Klosin and Vilgalys (2022) developed the panel data case. Details in Table A3.

Table 7. DML-Panel without Instrument

Variables	K=2		K=5	
	TFP Cobb Douglas PF	TFP Tran slog PF	TFP Cobb Douglas PF	TFP Tran slog PF
pcm_{it}	2.524 (4.593)	2.448 (3.953)	2.473 (34.422)	2.400 (3.577)
μl_{1it}	-0.174 (30.749)	-0.088 (30.962)	-0.171 (30.744)	-0.089 (30.814)
μinp_{1it}	0.151 (30.520)	0.279 (31.121)	0.159 (30.457)	0.294 (30.959)
μml_{2it}	-0.011 (31.796)	-0.069 (31.670)	-0.013 (31.996)	-0.064 (31.499)
μinp_{2it}	0.057 (31.219)	0.009 (31.196)	0.052 (31.343)	0.010 (31.074)

Source: Authors' calculations based on Table A3 of INEI-EEA (2024).
 *** represents significance <0.01; ** < 0.05 and * < 0.1. Standard errors in parenthesis.

Table 8. DML-Panel (Instrument RSI_{it})

Variables	K=2		K=5	
	TFP Cobb Douglas PF	TFP Tran slog PF	TFP Cobb Douglas PF	TFP Tran slog PF
pcm_{it}	1.280 (6.557)	1.125 (6.203)	1.232 (5.327)	1.073 (5.278)
μl_{1it}	0.253 (1.992)	0.288 (1.751)	0.236 (2.051)	0.283 (1.620)
μinp_{1it}	0.144 (1.119)	0.269 (1.801)	0.134 (1.086)	0.262 (1.502)
μml_{2it}	0.823 (4.320)	0.692 (3.982)	0.803 (3.617)	0.667 (3.407)
μinp_{2it}	0.655 (3.621)	0.557 (3.441)	0.638 (2.967)	0.536 (2.883)

Source: Authors' calculations based on Table A3 of INEI-EEA (2024).
 *** represents significance <0.01; ** < 0.05 and * < 0.1. Standard errors
 in parenthesis

Table 9. DML-Panel (Instrument RSI_{it-1})

Variables	K=2		K=5	
	TFP Cobb Douglas PF	TFP Tran slog PF	TFP Cobb Douglas PF	TFP Tran slog PF
pcm_{it}	1.207 (6.588)	1.125 (6.203)	1.162 (5.334)	1.005 (5.318)
μl_{1it}	0.273 (1.996)	0.292 (1.752)	0.256 (2.063)	0.287 (1.621)
μinp_{1it}	0.125 (1.126)	0.260 (1.808)	0.116 (1.106)	0.253 (1.507)
μml_{2it}	0.816 (4.324)	0.686 (3.983)	0.796 (3.616)	0.660 (3.412)
μinp_{2it}	0.659 (3.619)	0.564 (3.439)	0.643 (2.967)	0.543 (2.879)

Source: Authors' calculations based on Table A3 of INEI-EEA (2024).
 *** represents significance <0.01; ** < 0.05 and * < 0.1. Standard errors in parenthesis

Table 10. DML-Panel (*Market Share_{it}*)

Variables	K=2		K=5	
	TFP Cobb Douglas PF	TFP Tran slog PF	TFP Cobb Douglas PF	TFP Tran slog PF
pcm_{it}	1.596 (6.490)	1.667 (6.297)	1.538 (5.393)	1.600 (5.264)
μl_{1it}	0.291 (2.023)	-0.071 (2.096)	0.274 (2.081)	-0.068 (1.960)
μinp_{1it}	0.078 (1.122)	0.147 (1.794)	0.071 (1.075)	0.145 (1.525)
μml_{2it}	0.711 (4.299)	0.426 (3.948)	0.692 (3.603)	0.405 (3.446)
μinp_{2it}	0.590 (3.612)	0.337 (3.419)	0.574 (2.956)	0.321 (2.933)

Source: Authors' calculations based on Table A3 of INEI-EEA (2024).
 *** represents significance <0.01; ** < 0.05 and * < 0.1. Standard errors
 in parenthesis

Table 11. DML-Panel (Instrument $Market\ Share_{it-1}$)

Variables	K=2		K=5	
	TFP Cobb Douglas PF	TFP Trans log PF	TFP Cobb Douglas PF	TFP Trans log PF
pcm_{it}	0.859 (6.422)	0.505 (6.034)	0.828 (5.310)	0.481 (4.947)
μl_{1it}	0.238 (2.016)	0.740 (2.294)	0.221 (2.075)	0.723 (2.061)
μinp_{1it}	0.202 (1.177)	0.384 (1.948)	0.190 (1.128)	0.373 (1.642)
μml_{2it}	0.924 (4.368)	0.944 (4.213)	0.903 (3.695)	0.911 (3.629)
μinp_{2it}	0.733 (3.661)	0.783 (3.647)	0.715 (3.029)	0.754 (3.090)

Source: Authors' calculations based on Table A3 of INEI-EEA (2024).
 *** represents significance <0.01; ** < 0.05 and * < 0.1. Standard errors
 in parenthesis

For the period analyzed (2002-2019) and the sample of formal manufacturing firms considered, there are at least four examples that may support this result. First, most of the recent literature on firms' power in Latin America are oriented to the effects of market power (understood as excess of profits above of the competitive profit rates) to problems of inequality, governance, and the political economy of economic policy rather than to problems of efficiency, innovation, productivity, and technological change.¹⁷ Moreover, the handful studies in LAC on the relationship between market power and productivity do not address the problem of causality of that relationship but instead mainly present sample correlations.¹⁸

¹⁷ Among others, Durand (2004); North, Rubio, and Acosta (2020); Eslava, Melendez, and Urdaneta (2021); Tello (2022); nd Nercesian, Robles-Rivera, and Serna (2023).

¹⁸ For example, Rivera-Padilla (2023).

Second, in contrast with the previous case, recent studies on country or firms' productivity in Peru and/or LAC indicate that productivity is associated or influenced by the size of national and/or imported capital, the level of investment, tariff policies, free trade agreements, terms of trade, and growth of domestic output.¹⁹ Some of these results are also consistent with the panel data estimations of Tables A5 - A9. Moreover, author's studies on the role of innovation find that capital-labor ratio rather than innovation influence Peruvian formal firms' productivity.²⁰

Third, most Peruvian manufacturing branches are concentrated in light industries (garments, textiles, food and consumer goods) or involve a low degree of processing of primary goods (particularly mineral and agriculture products) with low levels of Product Complexity Indices (PCI, associated with the low level of the Peruvian Economic Complexity Index, ECI), which implies that technological and innovation aspects of manufacturing product development that affects firms' productivity are lacking.²¹

Fourth, the study of Durand (2004) on the analysis and features of the modern economic groups (EGs) in Peru reinforces all the previous examples. He makes the following observations:

1. The strongest corporate wealth of the EG today is less identified with specific sectors. Large conglomerates now command the economy, having a strong presence in certain niches where they first originated and expanded, and they are involved in multiple economic activities,²² a trend that is more marked among older groups.
2. Modern EGs have a stronger degree of power and higher levels of concentration than traditional economic groups (e.g., guano and agrarian oligarchy, fishing

¹⁹ Among others, Heresi (2024), Tello (2024, 2024a), and Tello & Tello-Trillo (2023). See also Tables from A5 to A9.

²⁰ For example, Tello (2024b, 2017, 2015).

²¹ The ECI and PCI have been developed by Hausmann, Hidalgo and associates (2009, 2013) and reported by the Harvard's Growth Lab's (2024). The economic complexity index of countries (ECI) is the holistic measure of the productive capabilities of a country. The ECI range usually is from -2.00-to 2.00. The ECI in 2021 for the top 20 developed countries is above 1.20. The ECI of Peru in 2020 is -0.87 and is in the lowest 30 percent of 131 countries. The PCI measures the diversity and sophistication of the productive know-how required to produce a product. In 2021 range between -3.4 and 2.3. The higher the number the more sophisticated is the product. For example, in 2021 the product Photographic plates and film, exposed and developed, other than motion-picture film has a PCI of 2.3, and Tin ores and concentrates, -3.31.

²² Activities as banking and financing, pharmacies, storage services, shopping centers, manufactures and others.

and industrial conglomerates that followed one another in the nineteenth and twentieth centuries). In terms of resources, yesterday's economic elite had hundreds of millions of dollars, and today's has billions.

3. Most EGs follow a process of vertical integration.
4. Thanks to a rapid accumulation of capital, the Peruvian EGs were able to expand their plants, buy or inaugurate others, establish alliances—mainly in the form of joint ventures—and begin to project themselves globally. Access to the financial system—which is preferentially enjoyed by Lima groups, but which is becoming widespread—and the use of a national and global stock market were key factors in the expansion and conglomeration process.²³
5. The economic and spatial—and therefore social—impact of EGs is today very strong, not in terms of employment but rather in terms of higher in consumption or the purchase of certain products, mainly final product.
6. Most manufacturing activities are concentrated on light industries (such as food products as a range of flour, oil products, soaps, palm oil, dairy products-milk, yogurt, juices, sugar, canned and frozen, and other agro-industries).²⁴

These four examples seem to suggest that resources and extra profits derived firms' market power, rather than being devoted to R&D and innovation activities²⁵ to increase firms' productivity, are instead devoted to expanding production activities through national and imported capital and foreign investments, and to exercising power over political actors and their economic policies.

²³ This expansion is expressed in the purchase or opening of companies abroad and the use of holding companies in various global markets.

²⁴ By 2021, the average PCI for the manufactured products made by Peruvian modern EGs is -0.85.

²⁵ Details of the low level of these activities in Peru relatively to LAC and other developed countries in Tello (2023).

5. Conclusions and Final Remarks

This paper uses seven standard market power indicators (price-cost margin, and six drawn upon the production approach) to estimate the effect market power on the rate of change of total factor productivity for a sample of formal manufacturing firms of Peru for period 2002-2019. After applying exogeneity tests and implementing panel data with fixed effects instrumental variable method, the results are not clear about the causal relationship between market power and firms' TFP. However, when the Double-Debiased machine learning causal method is applied for fixed effects panel data with and without instruments, firms' market power robustly seems not to cause their respective total factor productivity regardless of the market power indicators and instruments used.

Four examples are provided to support such causal relationship. First, recent relevant literature on Peru and other Latin American countries concentrates on the effects of market power on the political economy of economic policy, governance and inequality. Only a few studies deal with the efficiency and TFP of firms and countries, although they are based only on simple correlations analysis. Second, recent studies on country or firms' productivity in Peru and/or LAC indicate that productivity is associated with or influenced by the size of national and/or imported capital, the level of investment, tariff policies, free trade agreements, terms of trade, and growth of domestic output. Third, most Peruvian manufacturing is concentrated in low levels of Product Complexity Indices, PCI (associated with the low level of Peru's Economic Complexity Index, ECI), which implies that technological and innovation aspects of manufacturing product development that affects firms' productivity are lacking. Fourth, the features of modern Peruvian modern economic groups indicate that these groups devote their economic resources arising from their market power to expanding domestic and international markets on light manufactured industries intensive in the use of primary products (mineral and agricultural products) and using national and foreign capital for those purposes rather than R&D, innovation, and technological change.

The four examples, consistent with the causal result found, suggest that the relationship between market power and productivity needs to be analyzed on a case-by-case basis considering the product development of sectors, the influence and activities of firms and economic groups in

the domestic economy and foreign markets, and the level of development of the country's productive structure.

Annex Tables

Table A1. A Sample of the Literature of the Effects of Market Power on Firms' TFP and Markups Estimations			
No.	Authors	Description	Main Results
1	Rivera-Padilla (2023)	Mexico. The author uses simple correlations coefficients to estimate the relationship among markups growth, growth of output, value added, and labor productivity growth of 67 industries at the 3-digit sector level using national accounts data from Mexico, period 1997 to 2019. Mark ups are measure by the ratio between real output value and total cost.	The author finds a positive correlation between increases in markups and growth of output, value added, and labor productivity at the 3-digit sector level using national accounts data from Mexico. He concludes that the findings provide new evidence that a rise of market power can be associated with positive welfare effects and not only with negative outcomes of reduced competition.
2	Steinbrunner (2023)	This study examines the non-linear relationship between productivity growth and market power, using data on Central European manufacturing firms, from 2009 to 2017. TFP is measured through a PF (Olley & Pakes 1996) and market power by the returns of sales and the index of Lerner using the De Loecker & Warzynski (2012) method.	They show three results: i) a concave relationship between both variables; i.e., low levels of market power increase firm' TFP growth and high levels will increase it; ii) firms in competitive industries respond more sensitively to market power; and iii) fiercer competition does not widen the gap to the frontier, supporting the basic oligopoly models.
3	Battiat, Marvasi, Jona-Lasinio, Sopranzetti (2021)	This paper uses national accounting data, period 2008-2017, to investigate the relationship between markup and TFP for four major EU countries: France, Germany, Italy, and Spain. Markup is measure by the ratio of total gross output over total variable cost. They argue (pp.5) that: the association between markups and productivity is of primary importance to gauge whether increased concentration and market power represent a major concern. However, theoretical considerations show that the relation between these variables is non-trivial, and causality can go in either direction, implying that the issue is mainly empirical. The sign of the relation between market power and productivity depends on the degree of market power.	They find: i) EU countries are differentiated and followed different trends relative to the US, and the upward markup trend is less pronounced than in the US; and ii) markups are positively correlated with productivity, investments, and innovation, suggesting a larger role for the most efficient firms that might increase efficiency.
4	Dai, Li, Cai (2018)	Based upon Klette (1999) and unbalanced firms panel data from China from seven food and tobacco sectors for 17 years (from 1995 to 2011), the authors examine the relationships between market power, scale	They find i) all the seven food industries and the tobacco sector are characterized with significant market power; China's cigarette industry has a markup almost five times as the smallest one of the rest

Table A1. A Sample of the Literature of the Effects of Market Power on Firms' TFP and Markups Estimations

No.	Authors	Description	Main Results
		economy and productivity for such industries.	of industries; ii) China's soybean and cigarette sectors are shown to have scale economy, with return to scale being larger than 1, while the other five sectors are proved to have decreasing returns to scale; iii) there is a significant negative correlations between market power and scale economy in all sectors, and iv) a negative correlations between market power and productivity in most of the selected sectors.
5	Kiyota (2010)	The paper examines the relationship between productivity, markup, scale economies, and the business cycle and is based upon a simple econometric framework that permits simultaneous estimation of the changes in productivity, markup, and scale economies from a panel of firm-level data. The framework is then applied to Japanese firm-level data for 1994 - 2006.	The results indicate that productivity is procyclical even after the changes in markup and scale economies are controlled for. However, both markup and scale economies are neither procyclical nor countercyclical once the changes in productivity are considered.
6	Holmes & Schmitz (2010)	The authors present a survey of the question if competition spurs productivity. This question is central to economics and major figures in the profession, such as Schumpeter (1942), Stigler (1956), and Arrow (1962), have weighed in on the debate.	They conclude, for US industries, that all the studies found that increases in competition (or decreasing in firm's market power) led to increases in industry productivity. Plants that survived the increases in competition were typically found to have large productivity gains, and these gains often accounted for most overall industry gains.
7	Bloch & Kan Tang (2007).	They apply the Nadiri & Nandi (1999) methodology for Singapore's electronics industry using annual data for the period 1972-1997.	They find a negative contribution of markups on TFP growth. This negative markup effect possibly resulted from increasingly competitive forces that erode output price and markup for the industry.
8	Nadiri & Nandi (1999)	They examine the sources of productivity growth for the U.S. telecommunications industry from 1935 to 1987. They use a structural model that accounts for both changes in the cost and the demands of the industry.	They find that the contribution of markup is insignificant before the middle of the 1960s, but it increases subsequently. It represents over 50% of the measured TFP growth since 1975. The contribution of markup to TFP fluctuates considerably over time and has the same movement as that of

Table A1. A Sample of the Literature of the Effects of Market Power on Firms' TFP and Markups Estimations			
No.	Authors	Description	Main Results
			conventionally measured TFP growth rate.

Source: Authors' compilation based on cited sources.

Table A2. Methodology of Calculation of Productivity and Market Power Indicators

To calculate productivity for each firm, the following stochastic production function of the company is proposed:

$$[A1] \quad Q_{it} = F(A_{it}, V_{it}; \epsilon_{it}) ; i = 1, \dots, N ; t = 1, \dots, T$$

where Q_{it} represents the real production in 2007 soles of firm i in period t , A_{it} represents the level of total factor productivity of the same firm and ϵ_{it} is an uncontrolled stochastic term. V_{it} is a vector that represents the set of production factors (capital, labor and intermediate goods) that the firm uses for the production of the good. The specification proposed for this research work is a Cobb-Douglas function in logarithm that takes the following form:

$$[A2] \quad q_{it} = \beta_0 + \beta_l \cdot l_{it} + \beta_k \cdot k_{it} + \beta_m \cdot m_{it} + \omega_{it} + \epsilon_{it}$$

To solve the specification, this work uses the De Loecker approach, DL (De Loecker 2011, Tello & Tello-Trillo 2023), with two added assumptions: the existence of a CES production to materialize a standard horizontal product differentiation demand system in the following equation:

$$[A3] \quad Q_{it} = Q_{st} \left(\frac{P_{it}}{P_{st}} \right)^{n_s} \exp(\varrho)$$

Equation (A3) indicates the relationship between each production Q_{it} of the firm “ i ” depending on its own price P_{it} , the average price of the industry “ s ” P_{st} , the demand of the industry Q_{st} and unobserved demand shocks ϱ . It implies a constant markup over marginal cost in each segment or the industry $\frac{n_s}{n_s+1}$ (or Lerner index $\frac{1}{n_s}$), generating different demand elasticities for each segment.

In order to work with multiproduct firms, the second assumption suggests that the inputs L_{it} , K_{it} and M_{it} are constant for each product of the firm. If we suppose $R_{it} = \sum_j^{n_i} P_{ijt} \cdot Q_{ijt}$ and $r_{it} = R_{it}/P_s$; equation (A2) can be transformed into:

$$[A4] \quad \ln r_{it} = \beta'_l l_{it} + \beta'_m m_{it} + \beta'_k k_{it} + \beta_{np} np_{it} + \tau tr_{it} + \sum_s \beta_s q_{st} + \sum_j \beta_j D_{ij} + \omega_{it}^* + \varrho_{it}^* + \epsilon_{it}$$

In the specification, each input coefficient $\beta'_{input} = \frac{n_s+1}{n_s} \beta_{input}$, $\omega_{it}^* = \frac{n_s+1}{n_s} \omega_{it}$, $\varrho_{it}^* = \frac{1}{|n_s|} \varrho_{it}$, $\beta_s = \frac{1}{|n_s|}$. np_{it} represents the number of products of the firm. D_{ij} is the firm that sells a specific product i . Finally, q_{st} and tr_{it} takes the value of total production of sector “ s ” and the average preferential tariffs. To solve equation (A4), the estimation is solved in stages:

a) First stage

A quadratic polynomial $\varphi_{np,t}$ is aggregate in equation A8 that include a quadratic expression $h(\beta'_l, \beta'_m, \beta'_k)$:

$$[A5] \quad \ln r_{it} = \varphi_{np,t}(\beta'_l, \beta'_m, \beta'_k, \beta_{np}, \tau, \beta_s, \beta_j, h(\cdot)) + \epsilon_{it}$$

The OLS results generate the estimated value of $\widehat{\varphi_{np,t}}$ and is retained the lagged variable $\widehat{\varphi_{np,t-1}}$.

b) Second stage

From equation (A4) and using [A5], ω_{it}^* is estimated with another OLS regression:

Table A2. Methodology of Calculation of Productivity and Market Power Indicators

$$[A6] \ \omega_{it}^* = \widehat{\varphi_{np,t}} - \beta'_l l_{it} + \beta'_m m_{it} + \beta'_k k_{it} + \beta_{np} np_i + \tau tr_{it} + \sum_s \beta_s q_{st} + \sum_j \beta_j D_{ij}$$

c) Third stage

Assuming that the transformed TFP depends on its lagged information ω_{it-1}^* , lagged trade protection tr_{it-1} and a stochastic error $v_{it}(\beta'_l, \beta'_m, \beta'_k, \tau, D_{ij})$, the next equation (A7) is resolved:

$$[A7] \ \omega_{it}^* = g_t(\omega_{it-1}^*, tr_{it-1}) + v_{it}$$

Calculated v_{it+1} . The term v_{it} is not correlated with tr_{it} and tr_{it-1} .

d) Fourth stage

After the identification of $g_t(\cdot)$, the GMM is calculated:

$$[A8] \ E \left\{ v_{it+1}(\beta'_l, \beta'_m, \beta'_s, \tau, \beta_j) \begin{pmatrix} m_{it} \\ k_{it+1} \\ q_{st} \\ qr_{it+1} \\ D \end{pmatrix} \right\} = 0$$

In addition to the parameters estimated, $\widehat{\beta}_s$ allows us to calculate the elasticities of each sector given $\beta_s = \frac{1}{|n_s|}$. Now the TPF can be calculated in equation [A9].

$$[A9] \ \widehat{\omega}_{it} = (\widehat{\ln r_{it}} - \widehat{\beta}_l' l_{it} - \widehat{\beta}_m' m_{it} - \widehat{\beta}_k' k_{it} - \widehat{\beta}_{np} np_i - \widehat{\beta}_s q_{st} - \widehat{\tau} tr_{it}) \left(\frac{\widehat{\eta}_s}{\widehat{\eta}_s + 1} \right)$$

The process for trans log production functions is similar with a change in the input variables in equations (A2) and (A4) to match with a trans log production function.

Additionally, the calculation of market power is executed following De Loecker & Scott (2022), De Loecker & Warzynski (2012), and Tello & Tello-Trillo (2023). The process begins with the determination of the production function Q_{it} , which depends on the production factors and the productivity of the companies. Subsequently, it is assumed that each firm “i,” in period “t,” seeks to solve a Lagrange function Lg_{Cit} of cost minimization, given a production level $\bar{Q}_{it}$:

$$[A10] \ Lg_{Cit} = w_{it} l_{it} + p m_{it} m_{it} + r_{it} \bar{k}_{it} + \lambda_{it} (\bar{Q}_{it} - Q_{it}(l_{it}, m_{it}, \bar{k}_{it}, \omega_{it}))$$

where L_{it}, M_{it}, K_{it} are the production factors of employment, intermediate inputs and capital, respectively. The coefficients $w_{it}, p m_{it}, r_{it}$ represent the price of the factors and λ_{it} ; the marginal cost production given the production level. Under the assumption described in De Loecker & Warzynski (2012) that capital is a dynamic input, and that $Q_{it}(\cdot)$ is continuously and doubly differentiated with respect to its arguments, it is proposed that the first order condition of equation (A10) with respect to the non-dynamic input (it can be employment or intermediate inputs, which we will define as V_{it} while the price of the input will be defined as P_{it}^V), reassigning some values and multiplying both sides by $\frac{V_{it}}{Q_{it}}$ gives the result A11:

$$\frac{\partial Lg_{Cit}}{\partial V_{it}} = \frac{P_{it}^V}{\lambda_{it}}$$

Table A2. Methodology of Calculation of Productivity and Market Power Indicators

$$[A11] \quad \frac{\partial Lg_{Cit}}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{P_{it}^V V_{it}}{\lambda_{it} Q_{it}} ; V_{it} = L_{it}, M_{it}$$

The markup is defined as a fraction of the marginal cost calculated from the input V_{it} with the form: $\mu_{it}^V = \frac{P_{it}^V}{\lambda_{it}}$. This is due to the robustness of the indicator both for different models and the non-dependence on any form of price competition between firms. In consequence, if we define the elasticities of production on the input $\theta_{it}^V = \frac{P_{it}^V V_{it}}{\lambda_{it} Q_{it}}$ (since it implicates the minimization of the company's costs) equation (A11) changes to:

$$[A12] \quad \mu_{it}^V = \theta_{it}^V \cdot \left(\frac{P_{it}^V V_{it}}{P_{it} Q_{it}} \right)^{-1}$$

where μ_{it}^V represents the market power of company “i” in period “t” and with respect to an input V . The term θ_{it}^V indicates the output elasticity of input V , and the term $\frac{P_{it}^V V_{it}}{P_{it} Q_{it}}$ is the share on the input cost in total sales. The computation of θ_{it}^V , both labor factor and the intermediate input factor, arises from the calculation of the elasticities of the productivity models done in the productivity methodology. On the other hand, $\frac{P_{it}^V V_{it}}{P_{it} Q_{it}}$ is calculated using the estimated residuals ε_{it} from the first step regression in the calculation of productivities in the DL methods. The estimated residuals will allow us to correct the value of the total observed production $\bar{Q}_{it}$ inside $P_{it} Q_{it} = \frac{P_{it} \bar{Q}_{it}}{\exp(\varepsilon_{it})}$

Table A3. Machine Learning Panel Data Methodology

Introduction

Klosin and Vilgalys (2022) developed a method for estimating continuous treatment effects with a panel data setting. This methodology employs tools from the Machine Learning literature, particularly those works related to double-debiased machine learning (DML). This method is used in this article, and this appendix briefly presents the procedures that constitute it.

Methodology

Let N be the number of firms, T_i the number of periods of the firm i , L the number of groups into which the data is partitioned, $D_{i,t}$ the value of the continuous treatment variable for the firm i at the time t , $X_{i,t} = (X_{1,i,t}, \dots, X_{p,i,t})$ a vector of p covariates for the firm i at the time t , and let $y_{i,t}$ be the dependent variable for the firm i at the time t . Consider the equation of the regression model with panel data:

$$y_{i,t} = a_i + \gamma_0(D_{i,t}, X_{i,t}) + \varepsilon_{i,t}, i = 1, \dots, N, t = 1, \dots, T_i$$

The sample is divided into L groups, where each group contains all the observations of each company considered. This means that the division into groups is actually a division by companies. The set of companies in group l is denoted by I_l , for $l = 1, \dots, L$. Next, using the data on all the groups except one, the group l , each of the parameters is estimated. Therefore, the parameters estimated using all the companies except those in group l are denoted with a subscript l . For each l , and as a result of the estimation, the following is obtained for each i, t :

$$\hat{\tau}_{l,i,t} = \frac{\partial \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t})}{\partial D_{i,t}} + \hat{\alpha}_l(D_{i,t}, X_{i,t}, D_{i,t-1}, X_{i,t-1}) * (\Delta y_{i,t} - \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t}))$$

In the following, we show the estimation of each part of this equation.

Estimation of $\frac{\partial \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t})}{\partial D_{i,t}}$ and $\Delta y_{i,t} - \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t})$

It is assumed that γ_0 takes the form of a polynomial in the variables $D_{i,t}, X_{i,t}$. In this article we assume that γ_0 has the form of a polynomial of degree 3, we write $\gamma_0(D_{i,t}, X_{i,t})$, and its derivative. We omit using the subscripts i, t to lighten the notation, and X_i will replace $X_{i,j,t}$:

$$[1] \quad \gamma_0(D, X) = v_1 D + v_2 D^2 + v_3 D^3 + \sum_{i=1}^p b_{i,1} X_i + b_{i,2} X_i^2 + b_{i,3} X_i^3 + D(b_{i,4} X_i + b_{i,5} X_i^2 + b_{i,6} X_i^3) + \dots + D^2(b_{i,7} X_i + b_{i,8} X_i^2 + b_{i,9} X_i^3) + D^3(b_{i,9} X_i + b_{i,10} X_i^2 + b_{i,11} X_i^3)$$

In order to illustrate the procedures more clearly, we will assume that γ_0 takes the form of a polynomial of degree 2, $T_i = T$ and that $p = 1$. Then we have:

$$[2] \quad \gamma_0(D_{i,t}, X_{i,t}) = \beta_1 D_{i,t} + \beta_2 X_{i,t} + \beta_3 D_{i,t}^2 + \beta_4 D_{i,t} X_{i,t} + \beta_5 X_{i,t}^2$$

$$[3] \quad \Delta \gamma_0(D_{i,t}, X_{i,t}) = \beta_1 \Delta D_{i,t} + \beta_2 \Delta X_{i,t} + \beta_3 (D_{i,t}^2 - D_{i,t-1}^2) + \beta_4 (D_{i,t} X_{i,t} - D_{i,t-1} X_{i,t-1}) + \beta_5 (X_{i,t}^2 - X_{i,t-1}^2)$$

$$[4] \quad \frac{\partial \Delta \gamma_0(D_{i,t}, X_{i,t})}{\partial D_{i,t}} = \beta_1 + 2\beta_3 D_{i,t} + \beta_4 X_{i,t}$$

If we denote $\beta = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$, we can write:

$$[5] \quad \gamma_0(D_{i,t}, X_{i,t}) = (1, D_{i,t}, X_{i,t}, D_{i,t}^2, D_{i,t} X_{i,t}, X_{i,t}^2) \cdot \beta$$

$$[6] \quad \Delta \gamma_0(D_{i,t}, X_{i,t}) = (0, \Delta D_{i,t}, \Delta X_{i,t}, D_{i,t}^2 - D_{i,t-1}^2, D_{i,t} X_{i,t} - D_{i,t-1} X_{i,t-1}, X_{i,t}^2 - X_{i,t-1}^2) \cdot \beta$$

$$[7] \quad \frac{\partial \Delta \gamma_0(D_{i,t}, X_{i,t})}{\partial D_{i,t}} = (0, 1, 0, 2D_{i,t}, X_{i,t}, 0) \cdot \beta$$

Let $b(D_{i,t}, X_{i,t})' = (1, D_{i,t}, X_{i,t}, D_{i,t}^2, D_{i,t} X_{i,t}, X_{i,t}^2)$, $\Delta b(D_{i,t}, X_{i,t})' = (0, \Delta D_{i,t}, \Delta X_{i,t}, D_{i,t}^2 - D_{i,t-1}^2, D_{i,t} X_{i,t} - D_{i,t-1} X_{i,t-1}, X_{i,t}^2 - X_{i,t-1}^2)$, $\Delta b_D(D_{i,t}, X_{i,t})' = (0, 1, 0, 2D_{i,t}, X_{i,t}, 0)$, then:

Table A3. Machine Learning Panel Data Methodology

$$[8] \quad \gamma_0(D_{i,t}, X_{i,t}) = b(D_{i,t}, X_{i,t})' \beta$$

$$[9] \quad \Delta \gamma_0(D_{i,t}, X_{i,t}) = \Delta b(D_{i,t}, X_{i,t})' \beta$$

$$[10] \quad \frac{\partial \Delta \gamma_0(D_{i,t}, X_{i,t})}{\partial D_{i,t}} = \Delta b_D(D_{i,t}, X_{i,t})' \beta$$

Then, the β 's must be estimated. Given the model, it is known that

$$[11] \quad \Delta y_{i,t} = \Delta \gamma_0(D_{i,t}, X_{i,t}) + \Delta \varepsilon_{i,t}$$

$$[12] \quad \Delta y_{i,t} = \Delta b(D_{i,t}, X_{i,t})' \beta + \Delta \varepsilon_{i,t}$$

Based on this, the following Lasso optimization problem can be solved to estimate the β 's (in the summation, the i 's corresponding to all the groups except group l are selected):

$$[13] \quad \hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left\{ \frac{L}{N(L-1)(T-1)} \sum_{i \in I_l} \sum_{t=2}^T (\Delta y_{i,t} - \Delta b(D_{i,t}, X_{i,t})' \beta)^2 + r |\beta|_1 \right\}$$

where r is the regularization parameter, which essentially penalizes the inclusion of variables through $|\beta|_1 = \sum_{j=0}^5 |\beta_j|$. After estimating the β 's, the squared error can be calculated in the group that was not used. This numerical value is denoted by:

$$L_Y(l, r) = \sum_{i \in I_l} \sum_{t=2}^T (\Delta y_{i,t} - \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t}))^2$$

This number gives us a way to measure the fit's performance for group l . The parameter r_L is chosen by minimizing the average (over the groups) of these quantities:

$$r_L = \frac{1}{N(T-1)} \sum_{l=1}^L L_Y(l, r)$$

Finally, the β 's obtained by solving [13] using r_L are used to estimate the following two quantities:

$$[14] \quad \frac{\partial \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t})}{\partial D_{i,t}} = \hat{\beta}_2 + 2\hat{\beta}_4 D_{i,t} + \hat{\beta}_5 X_{i,t}$$

$$[15] \quad \Delta \hat{\gamma}_l(D_{i,t}, X_{i,t}) = \hat{\beta}_2 \Delta D_{i,t} + \hat{\beta}_3 \Delta X_{i,t} + \hat{\beta}_4 (D_{i,t}^2 - D_{i,t-1}^2) + \hat{\beta}_5 (D_{i,t} X_{i,t} - D_{i,t-1} X_{i,t-1}) + \hat{\beta}_6 (X_{i,t}^2 - X_{i,t-1}^2)$$

Estimation of $\hat{\alpha}_l(D_{i,t}, X_{i,t}, D_{i,t-1}, X_{i,t-1})$

The following form is assumed for α_0 , which is $\alpha_0 = \Delta b(D_{i,t}, X_{i,t})' \rho_0$, where $\rho_0 = (\rho_0, \rho_1, \rho_2, \rho_3, \rho_4, \rho_5)'$ is a vector of parameters, and $\Delta b(D_{i,t}, X_{i,t})'$ is defined as before. Thus, we have:

$$\alpha_0 = \rho_1 \Delta D_{i,t} + \rho_2 \Delta X_{i,t} + \rho_3 (D_{i,t}^2 - D_{i,t-1}^2) + \rho_4 (D_{i,t} X_{i,t} - D_{i,t-1} X_{i,t-1}) + \rho_5 (X_{i,t}^2 - X_{i,t-1}^2)$$

The estimation $\hat{\rho}$ of ρ_0 is obtained by solving (here, the same assumption about the indices iii is made):

$$[16] \quad \hat{\rho} = \underset{\rho}{\operatorname{argmin}} \left\{ \frac{L}{N(L-1)(T-1)} \sum_{i \in I_l} \sum_{t=2}^T (\alpha_0(D_{i,t}, X_{i,t}, D_{i,t-1}, X_{i,t-1}) - \Delta b(D_{i,t}, X_{i,t})' \rho)^2 + r_\alpha |\rho|_1 \right\}$$

In Appendix B.4 of the reference paper on the estimation methodology, it is shown that this optimization problem is equivalent to the following:

$$[17] \quad \hat{\rho} = \underset{\rho}{\operatorname{argmin}} \{-2M\rho + \rho' Q \rho + r |\rho|_1\}$$

Where $M = E[b_D(D_{i,t}, X_{i,t})]$ and $Q = E[\Delta b(D_{i,t}, X_{i,t})' \Delta b(D_{i,t}, X_{i,t})]$. For estimation purposes, the sample forms of M and Q are introduced, obtaining the matrices:

$$[18] \quad M = \frac{L}{N(L-1)(T-1)} \sum_{i \in I_l} \sum_{t=2}^T b_D(D_{i,t}, X_{i,t})$$

$$[19] \quad Q = \frac{L}{N(L-1)(T-1)} \sum_{i \in I_l} \sum_{t=2}^T \Delta b(D_{i,t}, X_{i,t})' \Delta b(D_{i,t}, X_{i,t})$$

Following the quadratic form of [2], M is a 6x1 matrix while Q is 6x6. Given a value of the regularization parameter r , $\hat{\rho}$ is estimated using an iterative process.

Table A3. Machine Learning Panel Data Methodology

Given an initial value for $\hat{\rho}$ and $r = \frac{c_1}{\sqrt{\frac{N(L-1)}{L}}} \varphi^{-1} \left(1 - \frac{c_2}{2p} \right)$, where φ is the cumulative standard normal distribution

function, p is the dimension of the vector ρ , c_1 is a constant whose value is determined similarly to r_L and is explained later, and c_2 is a constant that is typically set to 0.1. The steps are as follows:

Step 1: Calculate the following vector:

$$[20] \quad \hat{D}_l = \left[\text{diag} \left(\frac{L}{N(L-1)} \sum_{i \in I_l} [\Delta b(D_{i,t}, X_{i,t}) \Delta b(D_{i,t}, X_{i,t})' \hat{\rho} - b_D(D_{i,t}, X_{i,t})]^2 \right) \right]^{1/2}$$

Step 2: Solve:

$$[21] \quad \hat{\rho} = \underset{\rho}{\text{argmin}} \{ -2M\rho + \rho' Q \rho + 2rc_3 |\hat{D}_{l,1} \rho_1| + 2r \sum_{j=2}^p |\hat{D}_{l,j} \cdot \rho_j| \}$$

where c_3 is a constant typically set to 0.1, and $\hat{D}_{l,j}$ is the j -th diagonal entry of $\hat{D}_l$. To solve this optimization process, fix an initial value of ρ , and then for $j = 1, \dots, p$:

Step 2.1: Calculate the loadings that do not depend on ρ_j :

$$[22] \quad z_j = \hat{Q}_{jj}$$

$$[23] \quad \pi_j = \hat{M}_j - \sum_{k \neq j} \rho_k \hat{Q}_{jk}$$

$\hat{G}_{jj}$ is the (j, j) entry of G , and M_j, ρ_k, G_{jk} are obtained analogously.

Step 2.2: Update ρ_j according to the following:

$$[24] \quad \rho_j = \frac{\pi_j + \hat{D}_{jj} r}{z_j} \quad \text{si } \pi_j < -\hat{D}_{jj} r$$

$$[25] \quad \rho_j = 0 \quad \text{si } \pi_j \in [-\hat{D}_{jj} r, \hat{D}_{jj} r]$$

$$[26] \quad \rho_j = \frac{\pi_j - \hat{D}_{jj} r}{z_j} \quad \text{si } \pi_j > \hat{D}_{jj} r$$

Steps 2.1 and 2.2 are repeated in that order until ρ converges, and then we return to step 1, where $\hat{D}_l$ is updated with the new value of $\hat{\rho}$ just obtained in step 2, and then back to step 2.

The estimation procedure consists of performing the process until $\hat{\rho}$ converges, meaning steps 1 and 2 are repeated until $\hat{\rho}$ changes minimally using some criterion, such as the Euclidean distance. The convergent value of $\hat{\rho}$ is denoted by $\hat{\rho}_l$.

Once $\hat{\rho}_l$ is obtained using the firms that do not belong to group l , the squared error of the estimation of ρ can be calculated on the observations of group l , which is:

$$L_\alpha(l, r(c_1)) = -2\hat{M}_l \hat{\rho} + \hat{\rho}' \hat{Q}_l \hat{\rho}$$

with:

$$[27] \quad \hat{M}_l = \sum_{i \in I_l} \sum_{t=2}^T b_D(D_{i,t}, X_{i,t})$$

$$[28] \quad \hat{Q}_l = \sum_{i \in I_l} \Delta b(D_{i,t}, X_{i,t})' \Delta b(D_{i,t}, X_{i,t})$$

Chernozhukov (2022) suggests choosing c_1 as the value that solves:

$$c_1^* = \underset{c_1}{\text{argmin}} \left\{ \frac{1}{N(T-1)} \sum_{l=1}^L L_\alpha(l, r(c_1)) \right\}$$

Finally, ρ is estimated with c_1^* for each group l to obtain $\hat{\rho}_l$ and thus $\hat{\alpha}_l(D_{i,t}, X_{i,t}, D_{i,t-1}, X_{i,t-1}) = \Delta b(D_{i,t}, X_{i,t})' \hat{\rho}_l$.

Instrumental variables methodology

For the estimation with instrumental variables, we adopt the 2SLS approach. Therefore, in the first stage we first regress $D_{i,t}$ on $X_{i,t}$ and the corresponding instrumental variable $I_{i,t}$. Then, in the second stage, the predicted values of $D_{i,t}$ are used as the variable of interest to explain the growth of productivity with the methodology above. In both stages it's included the control variables.

Table A4. Correlation between Market Power and Instrument Variables

Instruments	pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}
RSI_{it}	-0.077***	0.269***	0.234***	0.123***	0.151***
RSI_{it-1}	-0.076***	0.264***	0.229***	0.124***	0.149***
$Market\ Share_{it}$	0.022*	-0.016	0.118***	0.004	0.016
$Market\ Share_{it-1}$	0.022*	-0.021	0.096***	0.006	0.013

Source: Authors' calculations based on INEI-EEA (2024).

Table A5. Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019

TFP Production function ¹		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
μ_{it}	1.251*** (-0.051)	-0.087*** (-0.011)	0.067*** (-0.009)	-0.121*** (-0.032)	-0.044* (-0.026)		1.242*** (-0.052)	-0.075*** (-0.015)	0.146*** (-0.023)	-0.138*** (-0.032)	-0.058** (-0.026)
$\Delta \ln GDP_t$	1.058** (-0.493)	-1.057** (-0.511)	-0.607 (-0.52)	-1.597*** (-0.517)	-1.451*** (-0.518)		1.145** (-0.502)	-1.540*** (-0.524)	-0.388 (-0.535)	-1.525*** (-0.525)	-1.383*** (-0.526)
TI_t	0.007*** (-0.001)	0.010*** (-0.001)	0.008*** (-0.001)	0.009*** (-0.001)	0.009*** (-0.001)		0.006*** (-0.001)	0.008*** (-0.001)	0.007*** (-0.001)	0.008*** (-0.001)	0.008*** (-0.001)
$tr_pref_output_{it}$	-0.018** (-0.008)	-0.011 (-0.009)	-0.006 (-0.009)	-0.009 (-0.009)	-0.009 (-0.009)		-0.020** (-0.008)	-0.011 (-0.009)	-0.019** (-0.009)	-0.01 (-0.009)	-0.011 (-0.009)
$tr_pref_input_{it}$	0.015 (-0.009)	0.012 (-0.01)	0.007 (-0.01)	0.01 (-0.01)	0.01 (-0.01)		0.017* (-0.009)	0.012 (-0.01)	0.018* (-0.01)	0.012 (-0.01)	0.013 (-0.01)
$tr_pref_out_DX_{it}$	0.020** (-0.009)	0.01 (-0.01)	0.008 (-0.01)	0.007 (-0.01)	0.008 (-0.01)		0.018* (-0.009)	0.006 (-0.01)	0.014 (-0.01)	0.005 (-0.01)	0.006 (-0.01)
$tr_pref_inp_DX_{it}$	-0.012 (-0.011)	-0.009 (-0.011)	-0.003 (-0.011)	-0.006 (-0.011)	-0.007 (-0.011)		-0.013 (-0.011)	-0.009 (-0.011)	-0.011 (-0.011)	-0.007 (-0.011)	-0.007 (-0.011)
$post_{it}$	-0.049	0.147	0.116	0.242	0.227		-0.023	0.264	0.129	0.271	0.256

Table A5. Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019

TFP Production function ¹		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
	(-0.217)	(-0.229)	(-0.23)	(-0.231)	(-0.231)		(-0.222)	(-0.234)	(-0.234)	(-0.234)	(-0.234)
$post_ln_Import_{it}$	-0.007 (-0.012)	-0.004 (-0.013)	-0.007 (-0.013)	-0.006 (-0.013)	-0.006 (-0.013)		-0.008 (-0.013)	-0.007 (-0.013)	-0.009 (-0.013)	-0.008 (-0.013)	-0.008 (-0.013)
ln_Import_{it}	-0.112*** (-0.02)	-0.096*** (-0.021)	-0.090*** (-0.021)	-0.085*** (-0.022)	-0.084*** (-0.022)		-0.095*** (-0.021)	-0.072*** (-0.022)	-0.077*** (-0.022)	-0.068*** (-0.022)	-0.067*** (-0.022)
$ln_KL_ratio_{it}$	-0.033 (-0.021)	0.037* (-0.022)	-0.008 (-0.022)	0.017 (-0.022)	0.005 (-0.022)		-0.041** (-0.021)	-0.005 (-0.022)	-0.057** (-0.023)	0.011 (-0.023)	-0.001 (-0.022)
$Ratio_KM_{it}$	0.630*** (-0.231)	0.858*** (-0.243)	0.835*** (-0.244)	0.884*** (-0.245)	0.880*** (-0.245)		0.621*** (-0.235)	0.884*** (-0.248)	0.805*** (-0.248)	0.878*** (-0.248)	0.877*** (-0.249)
DX_{it}	-0.019 (-0.021)	-0.038* (-0.023)	-0.040* (-0.023)	-0.039* (-0.023)	-0.040* (-0.023)		-0.016 (-0.022)	-0.041* (-0.023)	-0.039* (-0.023)	-0.037 (-0.023)	-0.038 (-0.023)
DFO_{it}	0.03 (-0.028)	-0.043 (-0.029)	-0.021 (-0.029)	-0.053* (-0.029)	-0.048 (-0.029)		0.035 (-0.028)	-0.045 (-0.03)	-0.018 (-0.03)	-0.049 (-0.03)	-0.044 (-0.03)
$DL1_{it}$	-0.304*** (-0.074)	-0.262*** (-0.078)	-0.309*** (-0.078)	-0.247*** (-0.078)	-0.259*** (-0.078)		-0.291*** (-0.075)	-0.253*** (-0.079)	-0.307*** (-0.08)	-0.231*** (-0.08)	-0.243*** (-0.08)

Table A5. Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019

TFP Production function ¹		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
$DL2_{it}$	-0.161** (-0.065)	-0.145** (-0.069)	-0.180*** (-0.069)	-0.139** (-0.069)	-0.147** (-0.07)		-0.155** (-0.066)	-0.138** (-0.07)	-0.199*** (-0.071)	-0.131* (-0.07)	-0.138* (-0.071)
$year_t$	-0.005 (-0.005)	-0.015*** (-0.005)	-0.013** (-0.005)	-0.013** (-0.005)	-0.012** (-0.005)		-0.006 (-0.005)	-0.016*** (-0.005)	-0.013** (-0.005)	-0.014*** (-0.005)	-0.013** (-0.005)
$_{cons}$	11.033 (-9.641)	30.259*** (-10.193)	26.542*** (-10.175)	26.618*** (-10.232)	24.606** (-10.228)		12.654 (-9.821)	31.846*** (-10.437)	28.040*** (-10.349)	28.456*** (-10.389)	26.225** (-10.387)
N	5643	5643	5643	5643	5643		5641	5641	5641	5641	5641
Firms FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations based on INEI-EEA (2024). Robust errors in parentheses. Three, two and one asterisks represent significant levels less than 1%, 5% and 10%, respectively.

¹ The methods used for the firms' TFP estimations are described in De Locker (2011a, b, c) for Cobb-Douglas PF and De Loecker & Warzynski (2012) for trans log PF. The estimated parameters of these PF are shown in Table A10 of the annex. The factor output elasticities of these production functions are also used to estimate the respective labor and inputs mark ups according to the method of De Loecker & Warzynski (2012). Raval's (2023b) markups are estimated according to his methodology, which is not based on such PF.

Table A6. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(RSI_{it})

TFP Production function	Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)		PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
μ_{it}	1.251*** (-0.051)	-0.087*** (-0.011)	0.067*** (-0.009)	-0.121*** (-0.032)	-0.044* (-0.026)	1.242*** (-0.052)	-0.075*** (-0.015)	0.146*** (-0.023)	-0.138*** (-0.032)	-0.058** (-0.026)
$\Delta \ln GDP_t$	1.058** (-0.493)	-1.057** (-0.511)	-0.607 (-0.52)	-1.597*** (-0.517)	-1.451*** (-0.518)	1.145** (-0.502)	-1.540*** (-0.524)	-0.388 (-0.535)	-1.525*** (-0.525)	-1.383*** (-0.526)
TI_t	0.007*** (-0.001)	0.010*** (-0.001)	0.008*** (-0.001)	0.009*** (-0.001)	0.009*** (-0.001)	0.006*** (-0.001)	0.008*** (-0.001)	0.007*** (-0.001)	0.008*** (-0.001)	0.008*** (-0.001)
$tr_pref_output_{it}$	-0.018** (-0.008)	-0.011 (-0.009)	-0.006 (-0.009)	-0.009 (-0.009)	-0.009 (-0.009)	-0.020** (-0.008)	-0.011 (-0.009)	-0.019** (-0.009)	-0.01 (-0.009)	-0.011 (-0.009)
$tr_pref_input_{it}$	0.015 (-0.009)	0.012 (-0.01)	0.007 (-0.01)	0.01 (-0.01)	0.01 (-0.01)	0.017* (-0.009)	0.012 (-0.01)	0.018* (-0.01)	0.012 (-0.01)	0.013 (-0.01)
$tr_pref_out_DX_{it}$	0.020** (-0.009)	0.01 (-0.01)	0.008 (-0.01)	0.007 (-0.01)	0.008 (-0.01)	0.018* (-0.009)	0.006 (-0.01)	0.014 (-0.01)	0.005 (-0.01)	0.006 (-0.01)
$tr_pref_inp_DX_{it}$	-0.012	-0.009	-0.003	-0.006	-0.007	-0.013	-0.009	-0.011	-0.007	-0.007

Table A6. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(RSI_{it})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
	(-0.011)	(-0.011)	(-0.011)	(-0.011)	(-0.011)		(-0.011)	(-0.011)	(-0.011)	(-0.011)	(-0.011)
$post_{it}$	1.070** (-0.468)	-0.690* (-0.406)	0.137** (-0.064)	1.153* (-0.62)	1.114* (-0.619)		0.982** (-0.476)	1.428 (-1.285)	0.298* (-0.153)	1.050* (-0.609)	1.080* (-0.656)
$post_ln_Import_{it}$	0.712 (-1.016)	0.874 (-1.454)	0.155 (-0.861)	1.164 (-1.468)	1.629 (-1.758)		0.649 (-1.034)	4.752 (-5.457)	0.483 (-1.019)	1.039 (-1.443)	1.642 (-1.849)
ln_Import_{it}	0.007*** (-0.001)	0.014*** (-0.003)	0.008*** (-0.001)	0.005** (-0.002)	0.006*** (-0.002)		0.006*** (-0.001)	0.002 (-0.006)	0.006*** (-0.001)	0.004* (-0.002)	0.005** (-0.002)
$ln_KL_ratio_{it}$	-0.017* (-0.009)	-0.017 (-0.012)	-0.003 (-0.009)	-0.020* (-0.011)	-0.023* (-0.013)		-0.019** (-0.009)	-0.034 (-0.025)	-0.026** (-0.012)	-0.021* (-0.011)	-0.024* (-0.013)
$Ratio_KM_{it}$	0.014 (-0.009)	0.022 (-0.014)	0.003 (-0.01)	0.017 (-0.012)	0.016 (-0.012)		0.016* (-0.009)	0.02 (-0.019)	0.023** (-0.011)	0.019 (-0.012)	0.018 (-0.012)
DX_{it}	0.018* (-0.01)	0.025 (-0.016)	0.008 (-0.01)	0.021 (-0.013)	0.02 (-0.014)		0.015 (-0.01)	0.009 (-0.018)	0.021* (-0.013)	0.018 (-0.013)	0.018 (-0.014)
DFO_{it}	-0.011	-0.027	0.001	-0.015	-0.014		-0.012	0.01	-0.014	-0.015	-0.015

Table A6. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(RSI_{it})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
	(-0.011)	(-0.019)	(-0.012)	(-0.014)	(-0.014)		(-0.011)	(-0.026)	(-0.012)	(-0.014)	(-0.014)
$DL1_{it}$	-0.011	-0.313	0.014	-0.067	-0.158		0.031	-0.279	0.017	-0.019	-0.12
	(-0.238)	(-0.426)	(-0.248)	(-0.306)	(-0.344)		(-0.243)	(-0.62)	(-0.26)	(-0.304)	(-0.352)
$DL2_{it}$	-0.007	0.008	-0.007	-0.006	-0.007		-0.008	-0.012	-0.01	-0.007	-0.008
	(-0.012)	(-0.019)	(-0.013)	(-0.015)	(-0.016)		(-0.013)	(-0.024)	(-0.013)	(-0.015)	(-0.016)
$year_t$	-0.108***	-0.168***	-0.095***	-0.092***	-0.115***		-0.090***	-0.014	-0.086***	-0.074***	-0.098***
	(-0.023)	(-0.056)	(-0.022)	(-0.025)	(-0.031)		(-0.023)	(-0.062)	(-0.024)	(-0.025)	(-0.031)
N	5375	5375	5375	5375	5375		5372	5372	5372	5372	5372
Firms FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations based on INEI-EEA (2024). Authors' work. Robust errors in parentheses. Three, two and one asterisks represent significance levels less than 1%, 5% and 10%, respectively.

Table A7. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(RSI_{it-1})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
μ_{it}	-0.482 (-0.651)	0.287 (-0.408)	-0.06 (-0.078)	-0.427 (-0.552)	-0.527 (-0.702)		-0.578 (-0.666)	-0.707 (-0.896)	-0.168 (-0.185)	-0.509 (-0.559)	-0.668 (-0.766)
$\Delta \ln GDP_t$	-2.256* (-1.356)	-2.253 (-1.424)	-1.981** (-0.99)	-2.258* (-1.303)	-2.737 (-1.941)		-2.332* (-1.387)	-4.187 (-3.802)	-2.189* (-1.184)	-2.326* (-1.316)	-3.003 (-2.109)
TI_t	0.010*** (-0.002)	0.007** (-0.003)	0.009*** (-0.001)	0.010*** (-0.002)	0.010*** (-0.002)		0.009*** (-0.002)	0.011*** (-0.004)	0.009*** (-0.001)	0.010*** (-0.002)	0.010*** (-0.002)
$tr_pref_output_{it}$	-0.006 (-0.01)	-0.006 (-0.011)	-0.013 (-0.01)	-0.006 (-0.01)	-0.003 (-0.012)		-0.008 (-0.01)	-0.001 (-0.017)	-0.004 (-0.013)	-0.007 (-0.01)	-0.004 (-0.013)
$tr_pref_input_{it}$	0.009 (-0.01)	0.006 (-0.013)	0.014 (-0.011)	0.008 (-0.01)	0.008 (-0.011)		0.011 (-0.011)	0.009 (-0.012)	0.007 (-0.012)	0.01 (-0.01)	0.01 (-0.011)
$tr_pref_out_DX_{it}$	0.004 (-0.012)	0.001 (-0.015)	0.008 (-0.01)	0.004 (-0.012)	0.002 (-0.013)		0.001 (-0.012)	0.005 (-0.012)	-0.002 (-0.014)	0.001 (-0.012)	-0.001 (-0.014)
$tr_pref_inp_DX_{it}$	-0.005	0.002	-0.01	-0.004	-0.003		-0.005	-0.016	-0.004	-0.004	-0.003

Table A7. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(RSI_{it-1})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)		PCM	De Loecker (2022)		Raval (2023)		
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}	
	(-0.012)	(-0.017)	(-0.012)	(-0.012)	(-0.013)	(-0.012)	(-0.017)	(-0.012)	(-0.012)	(-0.013)	
$post_{it}$	0.314	0.431	0.299	0.316	0.388	0.358	0.493	0.361	0.361	0.458	
	(-0.278)	(-0.402)	(-0.259)	(-0.268)	(-0.334)	(-0.285)	(-0.424)	(-0.274)	(-0.273)	(-0.354)	
$post_ln_Import_{it}$	-0.006	-0.012	-0.006	-0.006	-0.006	-0.007	-0.005	-0.006	-0.008	-0.007	
	(-0.014)	(-0.017)	(-0.013)	(-0.013)	(-0.014)	(-0.014)	(-0.016)	(-0.014)	(-0.013)	(-0.014)	
ln_Import_{it}	-0.075***	-0.051	-0.081***	-0.083***	-0.071**	-0.056**	-0.096**	-0.059**	-0.066***	-0.051	
	(-0.027)	(-0.054)	(-0.023)	(-0.022)	(-0.029)	(-0.027)	(-0.043)	(-0.025)	(-0.022)	(-0.031)	
$ln_KL_ratio_{it}$	0.014	-0.121	0.008	0.059	0.059	0.008	0.02	0.049	0.062	0.066	
	(-0.029)	(-0.175)	(-0.024)	(-0.079)	(-0.081)	(-0.03)	(-0.044)	(-0.066)	(-0.08)	(-0.088)	
$Ratio_KM_{it}$	0.945***	0.856***	0.878***	0.951***	1.130**	0.953***	1.196**	0.896***	0.959***	1.189**	
	(-0.283)	(-0.271)	(-0.249)	(-0.275)	(-0.443)	(-0.29)	(-0.529)	(-0.258)	(-0.28)	(-0.471)	
DX_{it}	-0.048*	-0.049*	-0.040*	-0.037	-0.041*	-0.048*	-0.071	-0.036	-0.034	-0.039	
	(-0.026)	(-0.028)	(-0.023)	(-0.023)	(-0.024)	(-0.027)	(-0.05)	(-0.024)	(-0.024)	(-0.024)	
DFO_{it}	-0.074	-0.051	-0.066	-0.074	-0.086	-0.074	-0.088	-0.064	-0.074	-0.092	

Table A7. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(RSI_{it-1})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
	(-0.05)	(-0.034)	(-0.041)	(-0.048)	(-0.063)		(-0.051)	(-0.071)	(-0.041)	(-0.048)	(-0.068)
$DL1_{it}$	-0.254*** (-0.084)	-0.285*** (-0.09)	-0.231** (-0.092)	-0.194 (-0.123)	-0.161 (-0.163)		-0.238*** (-0.086)	-0.232** (-0.097)	-0.195* (-0.104)	-0.167 (-0.125)	-0.12 (-0.176)
$DL2_{it}$	-0.154** (-0.073)	-0.190** (-0.091)	-0.134* (-0.076)	-0.096 (-0.104)	-0.052 (-0.155)		-0.147** (-0.075)	-0.039 (-0.163)	-0.093 (-0.095)	-0.079 (-0.105)	-0.019 (-0.168)
$year_t$	-0.014** (-0.006)	-0.002 (-0.015)	-0.011** (-0.005)	-0.016** (-0.008)	-0.014** (-0.006)		-0.016** (-0.007)	-0.04 (-0.035)	-0.012** (-0.005)	-0.018** (-0.008)	-0.015** (-0.006)
N	5375	5375	5375	5375	5375		5372	5372	5372	5372	5372
Firms FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations based on INEI-EEA (2024). Robust errors in parentheses. Three, two and one asterisks represent significance levels less than 1%, 5% and 10%, respectively.

Table A8. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(MS_{it})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)		PCM	De Loecker (2022)		Raval (2023)		
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}	
μ_{it}	2.524*** (-0.295)	-3.626* (-2.007)	7.252 (-9.788)	-5.163*** (-1.525)	-5.898** (-2.4)	2.671*** (-0.297)	-1.465*** (-0.268)	-19.498 (-27.341)	-5.755*** (-1.726)	-5.039*** (-1.637)	
$\Delta \ln GDP_t$	3.493*** (-0.763)	10.271 (-6.868)	77.221 (-106.2)	-12.517*** (-3.549)	-17.022** (-6.63)	3.877*** (-0.777)	-7.360*** (-1.418)	-113.075 (-156.98)	-13.655*** (-3.99)	-14.613*** (-4.617)	
TI_t	0.005*** (-0.001)	0.034** (-0.015)	-0.044 (-0.073)	0.026*** (-0.006)	0.025*** (-0.007)	0.004*** (-0.001)	0.014*** (-0.002)	0.114 (-0.149)	0.027*** (-0.006)	0.021*** (-0.005)	
$tr_pref_output_{it}$	-0.027*** (-0.009)	-0.049 (-0.047)	0.346 (-0.49)	0.035 (-0.026)	0.059 (-0.041)	-0.030*** (-0.009)	0.011 (-0.015)	0.94 (-1.34)	0.038 (-0.028)	0.047 (-0.033)	
$tr_pref_input_{it}$	0.019* (-0.01)	0.071 (-0.057)	-0.419 (-0.591)	-0.018 (-0.026)	-0.017 (-0.035)	0.022** (-0.01)	0.005 (-0.016)	-0.652 (-0.941)	-0.019 (-0.029)	-0.011 (-0.03)	
$tr_pref_out_DX_{it}$	0.032*** (-0.01)	0.098 (-0.068)	0.008 (-0.114)	-0.048 (-0.03)	-0.057 (-0.043)	0.031*** (-0.011)	0.003 (-0.017)	-0.993 (-1.407)	-0.057* (-0.033)	-0.05 (-0.035)	
$tr_pref_inp_DX_{it}$	-0.017 (-0.011)	-0.114 (-0.08)	0.393 (-0.556)	0.029 (-0.03)	0.033 (-0.042)	-0.019 (-0.012)	-0.026 (-0.019)	0.407 (-0.599)	0.032 (-0.034)	0.026 (-0.036)	

Table A8. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(MS_{it})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
$post_{it}$	-0.315 (-0.239)	-2.55 (-1.88)	-10.279 (-14.41)	1.463** (-0.69)	2.173* (-1.132)		-0.322 (-0.246)	0.766* (-0.402)	14.634 (-20.409)	1.640** (-0.767)	1.901** (-0.881)
$post_ln_Import_{it}$	-0.008 (-0.013)	0.067 (-0.074)	-0.065 (-0.171)	-0.008 (-0.033)	-0.004 (-0.046)		-0.009 (-0.014)	-0.003 (-0.022)	0.121 (-0.249)	-0.01 (-0.037)	-0.005 (-0.04)
ln_Import_{it}	-0.140*** (-0.022)	-0.518** (-0.26)	-0.61 (-0.75)	-0.057 (-0.055)	0.072 (-0.099)		-0.126*** (-0.023)	-0.125*** (-0.038)	1.073 (-1.625)	-0.037 (-0.061)	0.067 (-0.078)
$ln_KL_ratio_{it}$	-0.067*** (-0.023)	1.540* (-0.858)	-0.906 (-1.25)	0.706*** (-0.216)	0.657** (-0.278)		-0.080*** (-0.024)	0.049 (-0.039)	6.566 (-9.223)	0.780*** (-0.244)	0.552*** (-0.194)
$Ratio_KM_{it}$	0.398 (-0.251)	0.882 (-1.16)	-1.569 (-4.328)	1.987*** (-0.703)	3.905*** (-1.505)		0.361 (-0.258)	1.569*** (-0.435)	6.555 (-8.613)	2.114*** (-0.779)	3.423*** (-1.116)
DX_{it}	0.003 (-0.023)	0.067 (-0.123)	-0.059 (-0.264)	-0.005 (-0.058)	-0.05 (-0.079)		0.008 (-0.024)	-0.107*** (-0.041)	0.148 (-0.394)	0 (-0.064)	-0.045 (-0.069)
DFO_{it}	0.107*** (-0.034)	0.039 (-0.146)	2.567 (-3.542)	-0.393*** (-0.127)	-0.511** (-0.215)		0.121*** (-0.035)	-0.140*** (-0.053)	-2.934 (-4.077)	-0.428*** (-0.142)	-0.438*** (-0.157)

Table A8. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(MS_{it})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{1it}	μl_{2it}	μinp_{2it}
$DL1_{it}$	-0.341*** (-0.079)	-0.044 (-0.391)	-4.688 (-6.035)	0.619* (-0.328)	0.921* (-0.555)		-0.332*** (-0.081)	-0.208 (-0.133)	6.677 (-9.774)	0.737** (-0.368)	0.760* (-0.405)
$DL2_{it}$	-0.165** (-0.069)	0.277 (-0.407)	-2.789 (-3.644)	0.561** (-0.275)	1.001* (-0.529)		-0.160** (-0.072)	0.08 (-0.125)	6.466 (-9.32)	0.651** (-0.308)	0.838** (-0.383)
$year_t$	0.002 (-0.005)	-0.136* (-0.073)	-0.122 (-0.161)	-0.063*** (-0.02)	-0.033* (-0.02)		0.002 (-0.006)	-0.070*** (-0.014)	0.089 (-0.158)	-0.069*** (-0.022)	-0.031* (-0.017)
N	5375	5375	5375	5375	5375		5372	5372	5372	5372	5372
Firms FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations based on INEI-EEA (2024). Robust errors in parentheses. Three, two and one asterisks represent significance levels less than 1%, 5% and 10%, respectively.

Table A9. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(MS_{it-1})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method		PCM	De Loecker (2022)		Raval (2023)		PCM	De Loecker (2022)		Raval (2023)	
		pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}	pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}
μ_{it}		-7.192*** (-1.568)	2.937*** (-1.058)	-22.294 (-70.531)	8.769*** (-3.264)	5.923*** (-1.854)	-7.347*** (-1.589)	2.365*** (-0.527)	15.237 (-13.121)	8.739*** (-3.169)	6.680*** (-2.282)
$\Delta \ln GDP_t$		-15.088*** (-3.255)	-10.734*** (-3.981)	-242.837 (-764.267)	17.659** (-7.393)	14.423*** (-5.256)	-15.268*** (-3.298)	8.673*** (-2.576)	86.178 (-75.441)	17.642** (-7.177)	16.517*** (-6.395)
TI_t		0.021*** (-0.004)	-0.011 (-0.008)	0.172 (-0.519)	-0.020* (-0.012)	-0.007 (-0.006)	0.020*** (-0.004)	-0.002 (-0.004)	-0.075 (-0.072)	-0.021* (-0.011)	-0.01 (-0.007)
$tr_pref_output_{it}$		0.041* (-0.024)	0.022 (-0.037)	-1.102 (-3.471)	-0.085* (-0.046)	-0.078** (-0.038)	0.04 (-0.025)	-0.048** (-0.024)	-0.756 (-0.647)	-0.087* (-0.046)	-0.089** (-0.044)
$tr_pref_input_{it}$		-0.013 (-0.024)	-0.038 (-0.043)	1.332 (-4.194)	0.059 (-0.045)	0.038 (-0.035)	-0.011 (-0.025)	0.025 (-0.025)	0.533 (-0.458)	0.061 (-0.044)	0.044 (-0.04)
$tr_pref_out_DX_{it}$		-0.059** (-0.028)	-0.065 (-0.048)	0.008 (-0.354)	0.104* (-0.055)	0.073* (-0.041)	-0.062** (-0.029)	0.012 (-0.026)	0.787 (-0.679)	0.101* (-0.054)	0.080* (-0.047)
$tr_pref_inp_DX_{it}$		0.023 (-0.029)	0.08 (-0.056)	-1.237 (-3.914)	-0.067 (-0.053)	-0.047 (-0.042)	0.023 (-0.029)	0.022 (-0.03)	-0.331 (-0.301)	-0.067 (-0.052)	-0.052 (-0.047)

Table A9. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(MS_{it-1})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}
$post_{it}$	1.717*** (-0.657)	2.451** (-1.239)	32.467 (-102.378)	-1.91 (-1.253)	-1.756* (-1.024)		1.776*** (-0.668)	-0.617 (-0.627)	-11.013 (-9.959)	-1.893 (-1.242)	-1.969* (-1.186)
$post_ln_Import_{it}$	-0.002 (-0.032)	-0.065 (-0.058)	0.176 (-0.743)	-0.004 (-0.055)	-0.008 (-0.047)		-0.003 (-0.033)	-0.015 (-0.034)	-0.108 (-0.157)	-0.004 (-0.055)	-0.011 (-0.052)
ln_Import_{it}	0.068 (-0.063)	0.265* (-0.154)	1.526 (-5.157)	-0.133 (-0.093)	-0.244*** (-0.091)		0.089 (-0.064)	0.021 (-0.059)	-0.961 (-0.798)	-0.117 (-0.092)	-0.249** (-0.105)
$ln_KL_ratio_{it}$	0.194*** (-0.069)	-1.246*** (-0.458)	2.789 (-8.856)	-1.198*** (-0.455)	-0.659*** (-0.22)		0.190*** (-0.07)	-0.101* (-0.06)	-5.145 (-4.429)	-1.205*** (-0.444)	-0.750*** (-0.268)
$Ratio_KM_{it}$	2.167*** (-0.668)	0.838 (-0.999)	8.319 (-25.183)	-1.061 (-1.255)	-2.203* (-1.293)		2.186*** (-0.68)	-0.319 (-0.685)	-3.613 (-4.556)	-1.076 (-1.245)	-2.567* (-1.518)
DX_{it}	-0.163*** (-0.062)	-0.127 (-0.098)	0.017 (-0.836)	-0.1 (-0.099)	-0.031 (-0.081)		-0.163*** (-0.063)	0.075 (-0.064)	-0.183 (-0.26)	-0.095 (-0.098)	-0.028 (-0.09)
DFO_{it}	-0.476*** (-0.119)	-0.113 (-0.122)	-8.076 (-25.429)	0.547** (-0.253)	0.423** (-0.18)		-0.480*** (-0.12)	0.123 (-0.084)	2.222 (-1.97)	0.551** (-0.247)	0.488** (-0.214)

Table A9. IV-Fixed Effects Panel Data Estimates of the TFP Growth Rate ($\Delta \ln TFP_t$) of Manufacturing Companies, 2002-2019
(MS_{it-1})

TFP Production function		Cobb-Douglas					Trans log				
Mark up Method	PCM	De Loecker (2022)		Raval (2023)			PCM	De Loecker (2022)		Raval (2023)	
	pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}		pcm_{it}	μl_{1it}	μinp_{it}	μl_{2it}	μinp_{2it}
$DL1_{it}$	-0.06 (-0.198)	-0.449 (-0.326)	13.323 (-43.088)	-1.774*** (-0.65)	-1.462*** (-0.465)		-0.042 (-0.202)	-0.331 (-0.203)	-5.672 (-4.73)	-1.760*** (-0.638)	-1.600*** (-0.555)
$DL2_{it}$	-0.128 (-0.171)	-0.507 (-0.31)	7.941 (-25.735)	-1.373** (-0.539)	-1.318*** (-0.439)		-0.121 (-0.174)	-0.520*** (-0.198)	-5.32 (-4.505)	-1.366*** (-0.529)	-1.459*** (-0.525)
$year_t$	-0.051*** (-0.015)	0.089** (-0.042)	0.328 (-1.09)	0.074* (-0.039)	0.01 (-0.02)		-0.053*** (-0.016)	0.080*** (-0.025)	-0.092 (-0.086)	0.073* (-0.038)	0.012 (-0.022)
N	5375	5375	5375	5375	5375		5372	5372	5372	5372	5372
Firmas FE	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations based on INEI-EEA (2024). Robust errors in parentheses. Three, two and one asterisks represent significance levels less than 1%, 5% and 10%, respectively.

**Table A10. Coefficients of PF of De Loecker (2011a, b, c)
and De Loecker and Warzynski (2012)**

	Cobb Douglas PF	Tran slog PF
β_l	0.352	1.629
β_m	0.301	-0.402
β_k	0.282	-0.289
β_{l2}		0.031
β_{m2}		0.038
β_{k2}		0.023
$\beta_{lm\cdot}$		-0.091
β_{lk}		-0.020
$\beta_{km\cdot}$		0.001
β_{np}	-0.039	-0.039
τ	-0.025	-0.025
$\beta_l + \beta_m + \beta_k$	0.934	0.951 ¹

Source: Authors' calculations based on INEI-EEA (2024).

¹ Figures represents s the sum of the labor, input and capital output elasticities of the Trans log, which are 0.358, 0.252, and 0.341, respectively.

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