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ARTICLES IN THIS ISSUE

BOOK REVIEW

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The Philippine Review of Economics

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Decomposing the divergent post-pandemic productivity dynamics in Philippine manufacturing

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This paper draws on the 2019 to 2022 Annual Survey of Philippine Business and Industry to document new stylized facts on the post-pandemic dynamics of total factor productivity (TFP) in Philippine manufacturing. The estimates confirm the severe but heterogeneous productivity impact of Coronavirus disease 2019 (COVID-19) across sectors and regions, with low-tech industries suffering steep TFP declines. Recovery patterns were uneven: large manufacturers rebounded quickly after significant 2020 losses, medium-sized firms showed surprising resilience, while small firms struggled to regain their pre-pandemic productivity. Fixed-effects regressions show the significant and positive relationship of total hours worked, human capital, and tangible investment with TFP. In contrast, the productivity premia from research and development spending, financial access, and intangible investment are not robust after controlling for selection bias. This suggests that highly productive manufacturers compensated their reduced production capacity primarily through efficient labor utilization, skilled manpower, and capital deepening, which enabled agile business adjustments amidst pandemic shocks. Decomposition analysis also reveals the widening TFP gap between small and medium-sized firms, which accelerated between 2020 and 2022 due to increasing differences in endowment and persistent underlying traits. These findings underscore the constraints facing small manufacturers and the growing marginalization of their contribution to post-pandemic productivity growth.

JEL classification: D22, D24, L60
Keywords: Philippines, manufacturing, COVID-19 pandemic, total factor productivity, SMEs, Kitagawa–Oaxaca–Blinder decomposition

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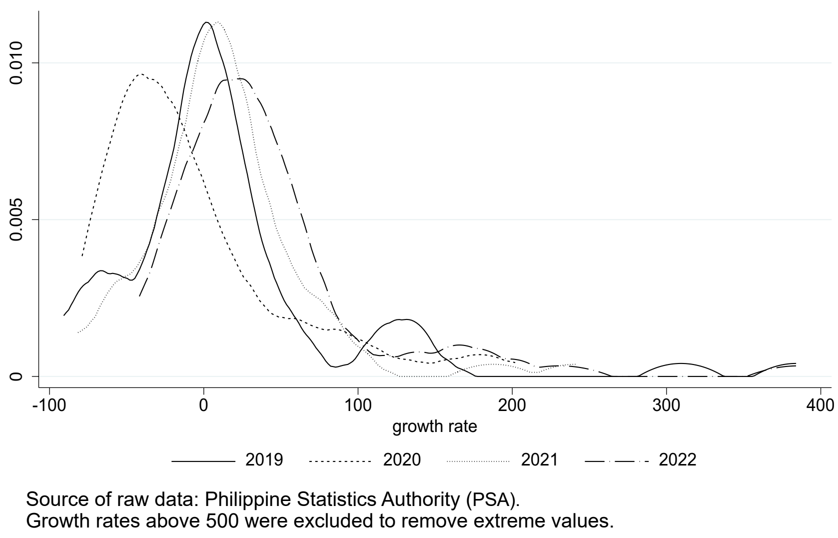
1. Introduction

Philippine manufacturing was adversely affected by Coronavirus disease 2019 (COVID-19) shocks, with real revenues (in 2018 prices) dropping by 14.23 percent in 2020. This was accompanied by similar sharp declines in the number of manufacturing establishments (-7.45 percent), employment (-13.18 percent), and labor productivity (-7.57 percent). Notwithstanding, manufacturing exhibited a strong post-pandemic rebound, with real revenues growing by 6.46 percent in 2021 and 19.26 percent in 2022. This is corroborated by Figure 1, which shows the kernel densities of the growth of real revenues of manufacturing subsectors at the three-digit level of the Philippine Standard Industry Classification (PSIC). The distribution first shifted to the left from 2019 to 2020 but quickly shifted back to the right from 2020 to 2021 and 2022. This indicates that many sectors have recovered from the temporary but adverse economic impacts of COVID-19 shocks. The Philippines implemented one of the longest and most stringent lockdowns during the pandemic, which generated simultaneous demand and supply disturbances that disrupted the productive activities of households and firms [Mendoza 2021].

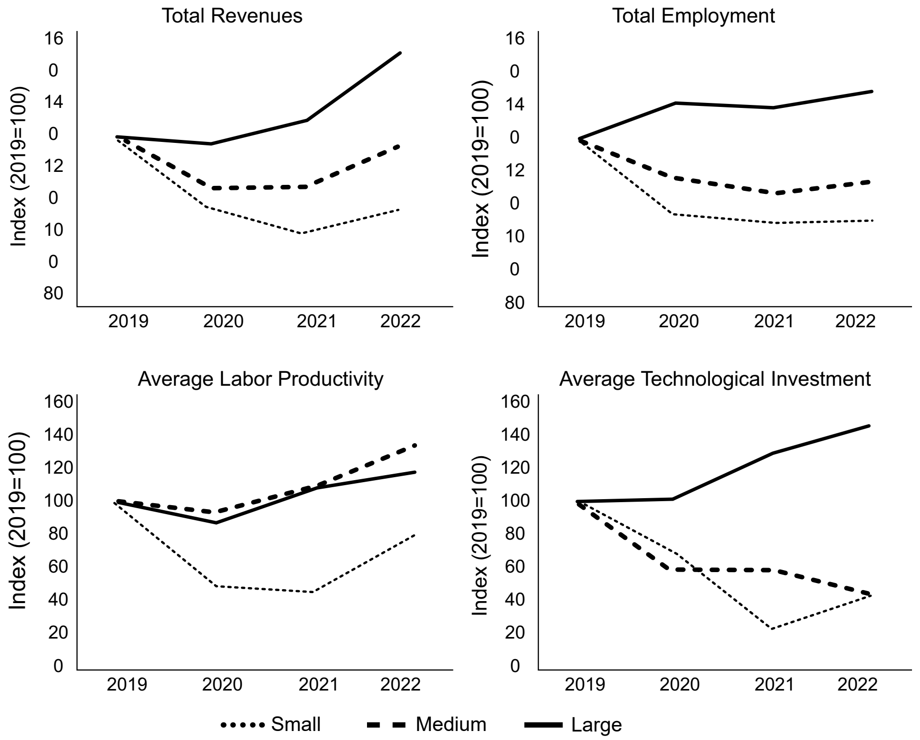
FIGURE 1. Kernel densities of manufacturing revenue growth rates of three-digit PSIC sectors, 2019-2022



Source of raw data: Philippine Statistics Authority (PSA).
Growth rates above 500 were excluded to remove extreme values.

Disaggregation of aggregate trends, however, shows a divergent post-pandemic performance of small and medium-sized establishments (SMEs) versus large manufacturers. As suggested by Figure 2, the strong manufacturing rebound in 2021 and 2022 was mainly driven by large establishments, while SMEs only sustained slow and weak recovery. The World Bank [2022] observed that Philippine establishments were operating in 2022 with fewer workers than before the pandemic, indicating a possible labor market scarring. The negative implications are not trivial, given that the share of SMEs in total manufacturing employment shrank from 54 percent in 2019 to just 34 percent in 2022. This translates to more than 321,000 unrecovered SME-related jobs after the pandemic, possibly resulting in severe income shocks and welfare losses in low-income households. Figure 2 also shows that the technological investment of SMEs stalled after 2020. This suggests that the scarring effect of the pandemic in the Philippines, if it exists, could partly be traced to the weak recovery of SMEs.

FIGURE 2. Indices of Philippine manufacturing indicators by size (2019 = 100)



Source of raw data: PSA.
Technological investment refers to the sum of capital expenditures on machinery and equipment, computer software and databases, and research and development (R&D).

Earlier documentations of the pandemic experience of Philippine establishments, particularly microenterprises, suggest that many businesses endured more than 50 percent revenue loss due to difficulties in input sourcing and supply chain coordination, liquidity constraints, and shortages of workers, which led to drastic cuts in operating hours (ADB [2020]; UNIDO [2020]; World Bank [2020]; Shinozaki and Rao [2021]). Most establishments (especially SMEs) closed temporarily, while many of those that remained open operated only at half capacity or less [ADB 2020]. These can be traced to the lockdown-induced economic hibernation enforced by the government to contain the pandemic. Dampened demand from consumers further deteriorated sales and cash flows. These supply and demand shocks were aggravated by the fact that many firms lacked business continuity plans to cope with an extraordinary crisis like COVID-19 [UNIDO 2020]. Nevertheless, some establishments responded innovatively to the disruptions by resorting to digital solutions (e.g., shifting to a work-from-home setup, e-commerce, and online payment methods) to overcome mobility restrictions caused by stringent containment policies [World Bank 2020]. The combination of firms' innovative responses and less strict community quarantine measures led to more businesses reopening by the end of 2020, albeit only partially [World Bank 2021]. Nevertheless, the lingering shocks caused by lockdowns continued to drag sales as establishments were forced to operate below full capacity in the face of limited mobility of suppliers, employees, and consumers. Uneven access to financing and government support further slowed down the recovery of firms. These difficulties disproportionately hit SMEs, many of which voluntarily closed at the height of the lockdowns and eventually exited the market permanently. By the end of 2020, manufacturing alone shed 2,146 SMEs—a 9 percent decline from 2019.

The adverse impact of COVID-19 on establishments has broad empirical support from recent cross-country, firm-level studies. For instance, Muzi et al. [2023] showed that less productive firms, especially SMEs, permanently exited the market during the crisis—evidence of a Schumpeterian cleansing effect. In their study of firms in 23 Southern and Eastern European countries, Janzen and Radulescu [2022] also found that small businesses endured bigger cuts in year-on-year sales growth due to lockdown stringency. Amin et al. [2025] attributed this to SMEs' larger vulnerabilities to supply, productivity, and financial shocks compared to large firms. Other studies suggest that SMEs with pre-pandemic innovative activities, better access to finance, crisis experience, and good institutional networks were less vulnerable to sales decline and market exit during the lockdowns (Chit et al. [2022]; Khan [2022]). Nevertheless, Doruk [2022] suggests that government assistance during the lockdowns helped firms, especially SMEs, weather the pandemic. On a macro level, Liu et al. [2021] found that survival is more likely for firms in countries with higher GDP per capita, less severe COVID-19 contagion, less stringent lockdowns, and a culture of future orientation.

The evidence from past global crises also suggests that smaller firms are less resilient to adverse economic shocks. For instance, Chen and Lee [2023] documented a divergence in the TFP growth of European SMEs and large firms after the Global Financial Crisis (GFC). The gap is partly traced to SMEs' exposure to more severe credit supply shocks and relatively larger reductions in intangible capital compared to large firms. Fort et al. [2013] added nuance to the crisis experience of small firms, observing that the decline in employment and market entry is more pro-cyclical among young small firms, while their older counterparts adjusted via layoffs rather than exit. Siemer [2019] showed that financial constraints during the GFC cut employment growth in US small firms by four to eight percentage points compared to large firms. This was mainly driven by constrained access to finance that heightened exit rates and suppressed entry of small and young enterprises. Chodorow-Reich [2013] found that US firms, especially SMEs, with pre-GFC ties to weak lending institutions experienced sharper employment cuts relative to establishments connected to healthier banks. Duval, Hong, and Timmer [2019] also observed from cross-country, firm-level data that establishments with fragile financial conditions before the GFC cut back on innovation spending during the crisis, which eventually weakened productivity growth.

The objective of this study is twofold. First, the paper generates updated estimates of production function parameters and TFP to provide stylized facts about the post-pandemic productivity trends in Philippine manufacturing. Second, the study formally analyzes the significant drivers of manufacturing productivity dynamics, especially among SMEs. This paper adds to the still limited literature that assesses the post-pandemic recovery of firms worldwide. Motivated by new establishment-level data released by the Philippine Statistics Authority (PSA) from 2019 to 2022, the current study investigates the seemingly two-speed recovery of establishments suggested by Figure 2. While the divergence between SMEs and large firms is not unexpected, the paper looks closer at the drivers of the deviant experiences of small and medium-sized manufacturers and identifies relevant strategies that smaller firms can adopt in order to catch up.

To our knowledge, this is the first documentation of the post-pandemic productivity dynamics of Philippine firms using official data, and among the very few micro-level studies that explore the topic in a developing-country setting. This paper also provides a descriptive analysis of updated estimates of production function parameters and TFP for Philippine manufacturing which are rarely available in the literature. The regressions show that efficient labor utilization, skilled manpower, experience, and tangible investment have robust positive and significant relationships with productivity. Focusing only on SMEs, the empirical analysis indicates a divergence in the productivity of small and medium-sized firms, which further widened between 2020 and 2022. This gap was traced to differences in endowment and persistent underlying traits, which dictated how well SMEs were able to ride the shockwaves generated by COVID-19 disruptions. These findings inform policy on designing post-crisis recovery programs for SMEs and for a robust manufacturing growth.

The rest of the paper proceeds as follows. Section 2 describes the data and methodology used in this study. Section 3 presents some stylized facts about the post-pandemic trends of TFP in Philippine manufacturing. Section 4 presents the results of the econometric analyses. Section 5 summarizes the paper and provides some policy insights.

2. Data and methodology

This section begins with a description of a newly assembled firm-level dataset used in the study. Section 2.2 sketches the control function approach for obtaining consistent estimates of production function parameters and TFP. Section 2.3 describes the econometric models used to analyze the key drivers of TFP and the decomposition technique for breaking down the post-pandemic productivity gap between groups of manufacturers.

2.1. Data

This study utilizes data from the Annual Survey of Philippine Business and Industry (ASPBI) from 2019 to 2022. The ASPBI covers 18 different sections classified based on the 2009 PSIC, although the current study focuses only on Section C (Manufacturing). The ASPBI is a nationally-representative survey that covers establishments in the formal sector of the economy. This excludes single proprietorship and single-establishment organizations with less than 10 employees. The sampling frame of the ASPBI was derived from the most recent List of Establishments, as summarized in Table 1. The ASPBI uses a stratified systematic sampling design with PSIC as the first stratification variable and employment size (i.e., micro, small, medium, and large), as the second stratification variable. This design reduces sampling bias and ensures that all important subgroups of the population of establishments are well-represented in the final sample. The region is the geographic domain of the ASPBI, which means that the survey can generate reliable estimates at this level.

TABLE 1. Number of establishments, 2019 to 2022

Year	List of establishments	ASPBI sampling frame	Estimated number of manufacturers
2019	1,000,524	336,712	24,270
2020	1,000,440	336,205	22,083
2021	1,079,093	349,071	25,279
2022	1,100,781	360,637	23,571

Source: PSA.

To form a panel dataset from 2019 to 2022, manufacturers across years were linked using their unique Enterprise Control Number (ECN). This longitudinal establishment dataset was then combined with the trade dataset to form the Merged Trade Transactions and Industry Censuses and Surveys (METTRICS) dataset. METTRICS enriches analysis by adding information on establishments' trading activities (e.g., monthly volume and value of imports and exports, destination of exports, origin of imports, and types of traded products based on the Philippine Standard Commodity Classification). For the 2019 to 2022 period, the METTRICS dataset for manufacturing contains 16,553 observations, 65.78 percent of which are small, 15.44 percent medium-sized, and 18.78 percent large. However, the panel is highly unbalanced, with only 1,030 establishments appearing in all years. Another limitation of the dataset is the absence of information on whether firms that do not appear in a given survey year have already exited the market or were merely excluded from the sample. The description and summary statistics of the variables used in this study are in Appendices 1 and 2, respectively.

2.2. Estimating total factor productivity

TFP measures how efficiently a firm can increase output using the same amount of labor and capital inputs [Avdiu 2022]. Understanding the dynamics of manufacturing TFP is particularly important, given its positive effect on aggregate economic performance. For instance, Jia et al. [2020] studied a sample of developed economies from 1970 to 2011 and found that manufacturing TFP influences economic growth both directly (via aggregate TFP) and indirectly (via capital and labor). However, the study did not find a similar effect coming from non-manufacturing TFP. In measuring firm-level productivity, a particular challenge arises due to the fact that firms typically choose the level of inputs (and output) after learning about their productivity. This results in the well-known simultaneity bias in production-function-based TFP estimation.

When the demand for intermediate inputs is assumed to be dependent on productivity, the log-linearized Cobb-Douglass production function can be expressed as:

$$y_{jt} = \beta_1 l_{jt} + \phi_{jt}\,(k_{jt}\,, m_{jt}) + \eta_{jt} \tag{1}$$

where $\phi_{jt}\,(k_{jt}, m_{jt}) = \beta_0 + \beta_2 k_{jt} + h(k_{jt}\,, m_{jt})$, $\omega_{jt} = h(k_{jt}\,, m_{jt})$, y_{jt} is the natural logarithm (ln) of value-added output of firm j at time t, l_{jt} is ln of labor (free variable), k_{jt} is ln of capital stock (state variable that is fixed in the short run), and m_{jt} is ln of intermediate inputs (proxy variable for unobserved productivity). The composite error term, μ_{jt}, consists of a time-varying productivity component specific to the firm, ω_{jt}, and a purely transitory component uncorrelated with input choices, η_{jt}. A key issue in the extraction of TFP from ordinary least squares (OLS) estimates of Equation 1 is that unobservable productivity shocks and input levels are correlated as shown by $\phi_{jt}\,(\cdot)$ and the control function $h(\cdot)$ [Petrin et al. 2004]. In particular, profit-maximizing firms adjust output level based on the direction of the shock which, in turn, has a corresponding effect on input usage (van Beveren [2012]; Bartelsman and Wolf [2014]). Input variables become endogenous when ω_{jt} is not fully extracted from μ_{jt}, leading to potentially inconsistent estimates.

The literature has advanced significantly in developing techniques that account for this correlation between input levels and unobservable productivity shocks (van Beveren [2012]; Bartelsman and Wolf [2014]). In particular, Olley and

Pakes (OP) [1996] and Levinsohn and Petrin (LP) [2003] developed the earliest approaches to deal with simultaneity issues in productivity and input choices by using the so-called control function approach.[1] Wooldridge [2009] added that the standard two-step semi-parametric procedure in the previous approaches can be simplified by using a generalized method of moments estimation in a one-step setup. Ackerberg et al. [2015] later proposed a modification to correct for the inherent functional dependence problems in the OP and LP methodologies.[2]

In this study, we apply the three-stage semi-parametric LP procedure to recover the unbiased $\widehat{\omega}_{jt}$ using the firm-level panel dataset described in Section 2.1. Total value-added output, number of employees, and capital stock (measured as the depreciation-adjusted book value of buildings, transport equipment, and machinery and equipment) are used as the dependent, free, and state variables, respectively. For the proxy variable, we use intermediate inputs defined as the combined costs of raw materials, electricity, and fuel. Monetary variables are adjusted using the industry GDP deflator with 2018 as the base year. While our dependent variable is revenue-based, controlling for aggregate price movements partly allows us to have a broad sense of the quantity-based TFP, which is considered a purer measure of technical efficiency [Avdiu 2022].

2.3. TFP regressions and decomposition

The TFP estimates are analyzed using regression models that link productivity to various firm-level covariates. The empirical literature has identified several key factors that drive, or at least correlate with, productivity variations across firms—research and development (R&D) and innovation, human capital accumulation, trade openness, strong institutions, and quality infrastructure (UNIDO [2007]; Kim and Loayza [2019]). Kim and Loayza [2019] and Ahmed and Bhatti [2020] also identified managerial quality, firm size, and access to finance as key determinants of productivity growth at the firm level. Investments in information and communication technology (ICT), intangible assets, and digitalization can help sustain firm-level productivity growth (Ahmed and Bhatti [2020]; Roth et al. [2022]). UNIDO [2007] added that market dynamics and resource reallocation within sectors can influence productivity.

Given the longitudinal dataset described in Section 2.1, we can estimate Equation 2 below, which accounts for time-invariant factors such as managerial quality, organizational cultures, and broad institutional endowments and constraints that affect firm productivity:

$$\ln TFP_{jt} = + \gamma_0 + \boldsymbol{x}_{jt}'\boldsymbol{\gamma} + u_j + \delta_t + \varepsilon_{jt} \tag{2}$$

[1] See Rovigatti and Mollisi [2018] for the technical details of the control function approach.

[2] The earliest estimation algorithms are implemented in Stata using the opreg (for OP) and levpet (for LP) commands. An alternative is the prodest command developed by Rovigatti and Mollisi [2018].

where $\ln TFP_{jt}$ is the ln of TFP of firm j at time t, $\boldsymbol{x}_{jt}$ is a vector of firm-level covariates, $\boldsymbol{\gamma}$ is a vector of coefficients, u_j is the unobserved time-invariant heterogeneity, δ_t controls for time fixed effects, and ε_{jt} is the error term. While standard random effects (RE) and fixed effects (FE) models can easily handle u_j, it is also important to recognize the potential selection bias that may arise from the systematic appearance or non-appearance of certain types of firms in the ASPBI. For instance, we only observe the productivity and other characteristics of firms that survived during the pandemic or those who willingly participated in the surveys despite the lockdowns. To account for this issue, the Heckman selection model adjusts the $\boldsymbol{\gamma}$ estimates in Equation 2 for possible selection bias by explicitly modelling the probability of observing a specific firm j based on its attributes.

The preceding TFP analysis is extended by implementing a decomposition method that breaks down the differential effects of the covariates in certain groups of firms. For instance, decomposition analysis can answer how much of the change in differences in the TFP levels between small, medium-sized, and large manufacturers can be attributed to compositional changes in the groups or to changes in the characteristics of firms. For this kind of exercise, the most popular approach is the Kitagawa–Oaxaca–Blinder (KOB) decomposition method. The basic principle behind the KOB decomposition is to obtain counterfactual estimates for the outcomes of one group, assuming it had the same endowment or structure as the reference group [Kröger and Hartmann 2021].

While the original KOB decomposition was designed for cross-sectional data, Kröger and Hartmann [2021] extended the approach to panel data, which accounts for the time-invariant unobservable effect.[3] This method provides the advantage of analyzing the impact of intertemporal dynamics on the mean differences of the groups being studied. For instance, Kröger and Hartmann's [2021] KOB method for panel data can answer the extent by which accumulated group differences in past tangible investments contribute to the current productivity gap. Similarly, the method can answer what factors account for the widening or narrowing TFP gap among small, medium-sized, and large manufacturers over time.

Given a panel dataset, the KOB decomposition from the perspective of Group 2 is expressed as follows:

$$\Delta \ln TFP_t = \underbrace{[E(\boldsymbol{X}_t^1) - E(\boldsymbol{X}_t^2)]\boldsymbol{\gamma}_t^2}_{\text{endowment effect}} + \underbrace{E(\boldsymbol{X}_t^1)(\gamma_t^1 - \gamma_t^2)}_{\text{structural effect}} + \underbrace{[E(\boldsymbol{X}_t^1) - E(\boldsymbol{X}_t^2)](\gamma_t^1 - \gamma_t^2)}_{\text{interaction effect}} + \underbrace{[E(\boldsymbol{u}^1) - E(\boldsymbol{u}^2)]}_{\text{effect of unobservables}}, \tag{3}$$

where $\boldsymbol{X}^G$ is a matrix of covariates, $\boldsymbol{\gamma}^G$ is a vector of slope coefficients, and $\boldsymbol{u}^G$ contains the time-invariant unobserved factors for group $G = \{1,2\}$. Kröger and

[3] This is implemented in Stata using the xtoaxaca module of Kröger and Hartmann [2021].

Hartmann [2021] explained that the endowment effect (*EE*) accounts for the mean TFP difference that is traced to differences in the two groups' time-varying characteristics; that is, the change in Group 2's TFP if its endowment level is equal to Group 1 at time t [Jann 2008]. The structural effect (*SE*) captures the gap due to differences in the model coefficients. Put differently, *SE* measures the change in Group 2's TFP if it had Group 1's coefficients [Jann 2008]. In this study, we can think of the coefficients as partial productivity returns. The interaction effect (*IE*) explains the difference due to the interaction of the two groups' different characteristics and coefficients. Equation 3 implies that KOB decomposition using panel regression models also attributes a portion of the differences between groups to *UE* or the effect of time-invariant or persistent underlying traits of firms.

The change in the TFP difference between the two groups and between two periods, say s and t for $s < t$, is given by:

$$\Delta \ln TFP = \Delta \ln TFP_t - \Delta \ln TFP_s = \Delta \ln TFP^1 - \Delta \ln TFP^2 \tag{4}$$

Depending on the approach, this "difference in differences" can be decomposed into changes in the two groups' TFP gap due to endowment, structural, and interaction effects. For instance, Kröger and Hartmann's [2021] "interventionist approach" proposed the following decomposition:

$$\Delta \ln TFP^1 - \Delta \ln TFP^2 = \Delta EE + \Delta SE + \Delta IE \tag{5}$$

where $\Delta EE = [E(\boldsymbol{X}_t^1) - E(\boldsymbol{X}_s^1)]\gamma_s^1 - [E(\boldsymbol{X}_t^2) - E(\boldsymbol{X}_s^2)]\gamma_s^2$, $\Delta SE = E(\boldsymbol{X}_s^1)(\gamma_t^1 - \gamma_s^1) - E(\boldsymbol{X}_s^1)(\gamma_t^2 - \gamma_s^2)$, and $\Delta IE = [E(\boldsymbol{X}_t^1) - E(\boldsymbol{X}_s^1)](\gamma_t^1 - \gamma_s^1) - [E(\boldsymbol{X}_t^2) - E(\boldsymbol{X}_s^2)](\gamma_t^2 - \gamma_s^2)$. Given no change in the initial differences in coefficients, ΔEE captures the contribution of the changes in the endowments between s and t to the overall TFP gap [Kröger and Hartmann 2021]. On the other hand, given no change in the initial differences in endowments, ΔSE measures the portion of the overall TFP gap that can be traced to adjustments in the coefficients between groups from period s to t. Kröger and Hartmann [2021] suggest that $\Delta UE = [E(\boldsymbol{u}_t^1) - E(\boldsymbol{u}_s^1)] - [E(\boldsymbol{u}_t^2) - E(\boldsymbol{u}_s^2)]$ should be accounted for when the group differentials in time-constant factors are substantial, which may be expected in an unbalanced panel.

3. Stylized facts

Table 2 summarizes the parameter estimates for the log-linearized Cobb-Douglass production function using the LP method. For comparison, we also showed the estimates using pooled OLS (POLS), FE, and RE regressions. Compared to LP1, LP2 controlled for the potential bias due to attrition. However, given our lack of information about true exit versus mere non-inclusion in the survey, misclassifying random missingness as attrition may also result in biased estimates. That said, we will use LP1 in succeeding TFP analyses given that the estimates are close (see Appendix 3). Table 3 confirms that on average, production technology in Philippine manufacturing is still labor intensive, as suggested by the higher elasticity of value-added output with respect to labor than with respect to capital. For the LP method, $\widehat{\beta_1}/\widehat{\beta_2} > 3$, indicating that production is at least three times more responsive to changes in labor than in capital. The second important observation is that the POLS and RE estimates for the labor coefficient are significantly larger than in other methods, confirming Levinsohn and Petrin's [2003] argument that OLS overestimates the parameters of free variables.

TABLE 2. Estimates of production function parameters using various methods

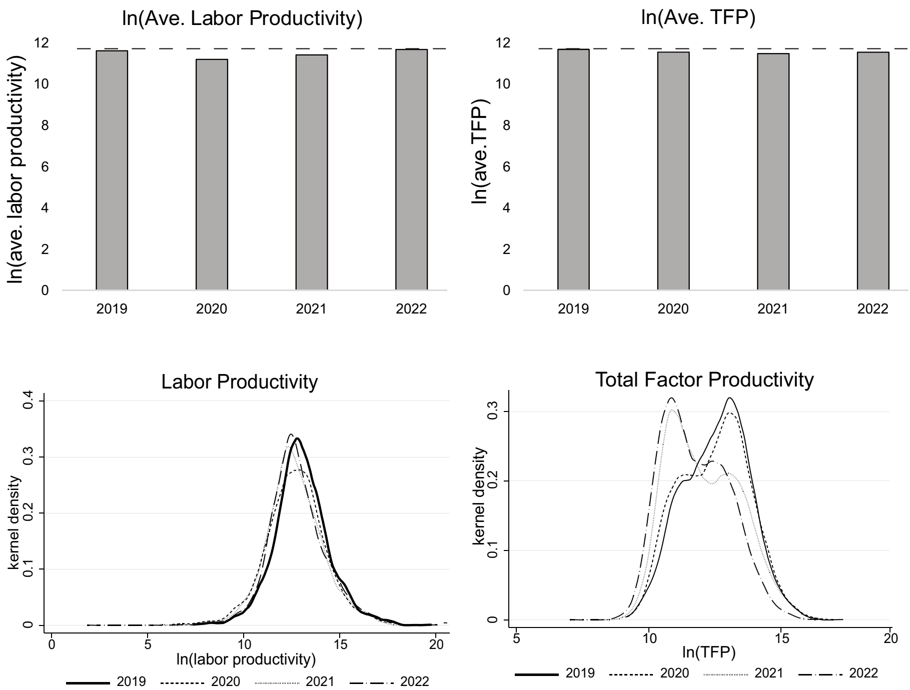
	POLS	RE	FE	LP1	LP2
Labor (ln)	0.886***	0.900***	0.471***	0.475***	0.475***
	(0.012)	(0.015)	(0.034)	(0.012)	(0.012)
Capital (ln, 2018 prices)	0.289***	0.236***	0.095***	0.142***	0.160***
	(0.009)	(0.010)	(0.012)	(0.024)	(0.024)
No. of observations	15,178	15,178	15,178	15,178	15,178
R-Squared	0.829	0.826	0.747	-	-

Source of raw data: PSA.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
POLS – Pooled OLS, RE – Random Effects, FE – Fixed Effects, LP – Levinsohn-Petrin
The dependent variable is ln of value-added output (in 2018 prices). All regressions include industry, region, and year controls. Numbers in parentheses are robust standard errors.

Figure 3 summarizes the evolution of manufacturing TFP before, during, and after the pandemic. For reference, we also showed the labor productivity dynamics from 2019 to 2022. The upper-right panel shows that average TFP dropped in both 2020 and 2021. Recovery was slow, with the average TFP in 2022 still below the 2019 level. Similar to the picture suggested by Figure 1, the distribution of manufacturing TFP in the lower-right panel shifted to the left from 2019 to 2020. This confirms the deterioration of firms' productivity at the height of exponential COVID-19 spread, stringent containment policy, and economic hibernation in 2020. The leftward shift continued through 2021, reflecting the delayed recovery of domestic manufacturing partly due to prolonged lockdowns. The TFP distribution in 2022 remained on the left of the 2019 curve, confirming our earlier observation that manufacturing productivity had been slow to recover to pre-pandemic levels. Another striking pattern is the change in the shape of the distributions, which became more dispersed and right-skewed after 2020. This hints at the two-speed, post-pandemic productivity trend, with relatively high-TFP (and possibly large) manufacturers recovering faster while low-TFP (and most likely small) firms still struggle to cope with the lingering effects of lockdowns and occasional surges in COVID-19 cases.[4]

[4] AMRO [2024] documented a possible scarring effect in the post-pandemic growth of the Philippine economy due to weaker growth in physical capital stock, TFP, and human capital.

FIGURE 3. Dynamics of productivity in Philippine manufacturing, 2019-2022



Source of raw data: PSA.

Table 3 summarizes the average TFP of major manufacturing sectors at the two-digit PSIC level. The erosion of manufacturing productivity in 2020 was observed across the board, demonstrating how the pandemic disrupted productive activities in almost all economic sectors. However, the impact of aggregate COVID-19 shocks was highly heterogeneous, with textiles, paper and paper products, and printing and reproduction of recorded media experiencing more than 40 percent reductions in average TFP. Variations in actual exposure and vulnerability to adverse shocks in input sourcing and supply chains, financing, and demand explain why some sectors fared worse than others. Production technology varies across industries, with relatively labor-intensive sectors severely affected by workers' loss of mobility due to lockdowns.

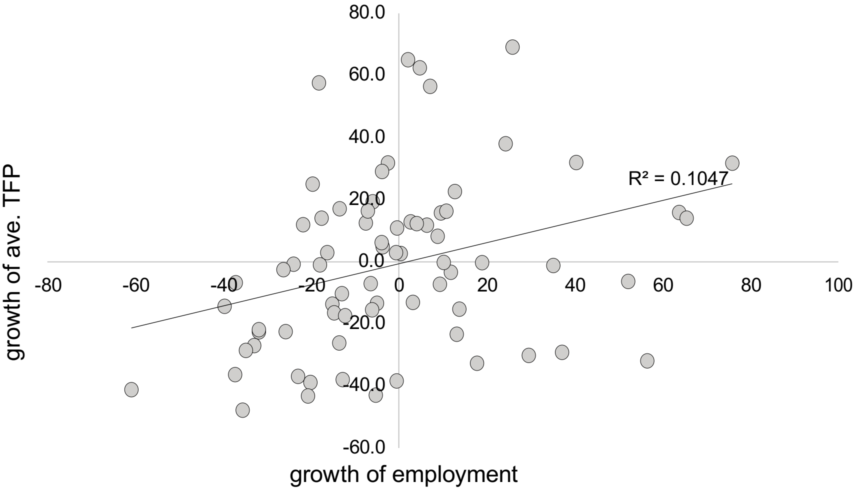
TABLE 3. Average TFP by manufacturing sector, 2019-2022

Two-digit industry description	Level (ln)				Year-on-Year Growth		
	2019	2020	2021	2022	2020	2021	2022
Food Products	12.1	11.8	11.7	11.8	-22.5	-13.3	15.8
Beverages	11.9	11.5	11.2	11.3	-32.6	-22.4	12.5
Tobacco Products	13.8	13.7	14.1	13.5	-13.1	56.6	-43.2
Textiles	13.0	12.3	12.3	12.5	-47.7	-3.4	16.4
Wearing Apparel	12.2	11.8	12.0	11.9	-36.3	22.7	-7.0
Leather and Related Products	12.6	12.1	12.6	12.2	-37.9	62.5	-30.1
Wood and Related Products (excl. Furniture)	12.2	12.1	12.1	12.2	-10.2	2.7	11.8
Paper and Paper Products	13.0	12.4	12.6	12.6	-42.9	25.1	-2.5
Printing and Reproduction of Recorded Media	12.0	11.5	11.3	11.5	-41.1	-13.6	16.3
Coke and Refined Petroleum Products	13.1	13.6	14.1	13.7	65.1	57.7	-31.9
Chemicals and Chemical Products	12.6	12.6	12.4	12.8	3.0	-16.4	38.1
Basic Pharmaceutical Products and Pharmaceutical Preparations	12.7	12.8	12.7	12.9	15.9	-14.3	32.0
Rubber and Plastic Products	12.8	12.5	12.7	12.6	-26.9	19.4	-7.2
Other Non-Metallic Mineral Product	12.8	12.3	12.4	12.4	-38.8	8.3	-1.2
Basic Metals	13.3	12.9	12.9	13.1	-36.9	-0.3	29.2
Fabricated Metal Products, except Machinery and Equipment	12.6	12.3	12.2	12.2	-21.8	-15.4	4.9
Computer, Electronic and Optical Products	13.8	14.1	13.9	14.0	31.8	-17.3	12.3
Electrical Equipment	13.0	13.0	13.0	13.1	-0.7	-6.3	14.1
Machinery and Equipment	12.7	12.7	12.4	12.9	-0.9	-23.3	69.2
Motor Vehicles, Trailers and Semi-Trailers	13.2	13.4	13.5	13.2	14.1	17.1	-29.1
Other Transport Equipment	12.6	12.9	12.9	12.8	31.9	3.0	-15.2
Furniture	12.2	11.9	11.9	12.0	-28.5	-0.2	10.9
Other Manufacturing	12.6	12.3	12.4	12.5	-26.1	12.9	6.2
Repair and Installation of Machinery and Equipment	12.3	12.2	11.8	11.9	-6.7	-38.3	12.0
Low Tech	12.2	11.8	11.7	11.8	-29.5	-10.7	13.8
Low-Medium Tech	12.8	12.4	12.4	12.4	-27.8	-5.0	3.1
High-Medium Tech	12.8	12.9	12.7	12.9	6.3	-10.2	19.8
High Tech	13.5	13.8	13.7	13.8	30.9	-10.5	11.7
All Sectors	12.4	12.1	12.0	12.1	-22.8	-11.2	14.0

Source of raw data: PSA.

As shown in Figure 4, the sectors that experienced the largest productivity losses in 2020 also cut back on labor. This is corroborated by Table 3, which shows that capital-intensive sectors such as coke and refined petroleum products, chemicals and chemical products, basic pharmaceutical products and pharmaceutical preparations, motor vehicles, trailers and semi-trailers, and other transport equipment posted positive average TFP growth in 2020. Moreover, the average TFP of low- and low-medium tech industries fell in 2020, while high-medium and high-tech industries still experienced productivity growth. This divergence implies that the pandemic shock disproportionately disrupted more labor-intensive and SME-dominated sectors while capital-intensive sectors exhibited greater resilience through better capabilities and favorable market position. The degree by which a production activity was considered essential during the pandemic may have also contributed to sectoral variations, with the likes of food and pharmaceuticals allowed to operate at full capacity despite mandatory factory shutdowns in most non-essential activities.[5] For instance, mean TFP, total revenues, and total employment of pharmaceutical manufacturing grew respectively by an average of 11.2 percent, 76.36 percent, and 21.50 percent from 2020 to 2022.

FIGURE 4. Growth of average TFP versus growth of employment across manufacturing sectors, 2020-2022



Source of raw data: PSA

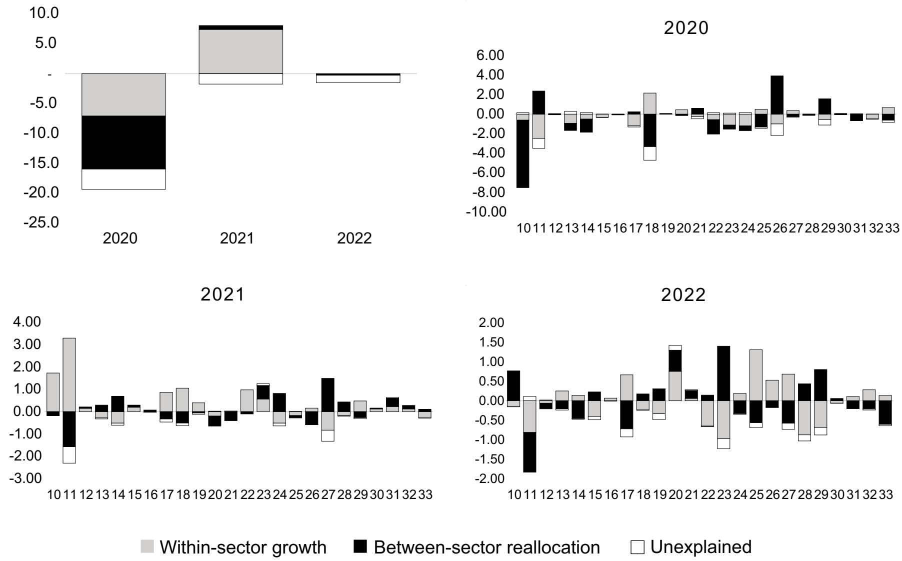
[5] In the Philippines, the following Category I sectors were allowed to operate at full capacity based on the official guidelines released on April 29, 2020 [OP-IATF 2020]: agriculture, fisheries, and forestry; food manufacturing and food supply chain businesses, food retail establishments such as supermarkets and grocery stores, food delivery services; health-related establishments; logistics; information technology and telecommunications; and media. Manufacturers of medicines, medical supplies, devices and equipment were also allowed to operate at full capacity.

Figure 5 decomposes the year-on-year change in manufacturing TFP per worker into within-sector growth and between-sector reallocation according to the following formula:

$$\frac{\Delta y_t}{y_{t-1}} = \frac{1}{y_{t-1}} \Big(\sum_i \Big[\underbrace{y_{i,t-1}(s_{i,t} - s_{i,t-1})}_{\text{between}} + \underbrace{s_{i,t-1}(y_{i,t} - y_{i,t-1})}_{\text{within}} + \underbrace{(s_{i,t} - s_{i,t-1})(y_{i,t} - y_{i,t-1})}_{\text{residual}} \Big] \Big)$$

where y_t is TFP per worker of the entire manufacturing sector at time t, $y_{i,t}$ is TFP per worker of subsector i at time t, $s_{i,t}$ is share of subsector i in total manufacturing employment at time t. The decomposition shows that the productivity decline in 2020 was mainly driven by negative between-sector reallocation and negative within-sector growth. The negative between-sector reallocation may be partly traced to the movement of workers to lower productivity sectors as manufacturers were forced to scale down operations during the lockdowns, while more traditional manufacturing activities in food and agribusiness were allowed to operate at full capacity. It is also possible that stringent containment policies encouraged the adoption of labor-saving technologies which displaced some workers in high-tech establishments. The negative within-sector growth in 2020 mostly originated from low- and medium-tech manufacturing which were more vulnerable to factory shutdowns, supply chain disruptions, and demand losses. These sectors are also dominated by SMEs which had fewer resources to adopt digital solutions to mobility restrictions. The unexplained source of TFP decline in 2020 may be partly attributed to firm exits and reallocations to precarious non-manufacturing jobs during the crisis. In 2021, within-sector growth—especially in food products, beverages, paper and paper products, printing and reproduction of recorded media, coke and refined petroleum products, rubber and plastic products, other non-metallic mineral products, motor vehicles, and trailers and semi-trailers—supported the rebound of manufacturing productivity. This is consistent with the observation of de Nicola et al. [2025] that productivity growth in East Asia and the Pacific, which includes the Philippines, has been mainly driven by within-firm changes. However, Figure 2 suggests that the recovery in 2021 was not sustained in 2022 due to heterogeneity in within-sector and between-sector growth. Large offsetting movements in within- and between-sector reallocations were observed in food products, paper and paper products, other non-metallic mineral products, fabricated metal products, computer, electronic and optical products, electrical equipment, machinery and equipment, and motor vehicles, trailers and semi-trailers. Chemicals and chemical products and basic pharmaceutical products and pharmaceutical preparations stood out in 2022 for having positive within- and between-sector growth in average TFP per employee.

FIGURE 5. Decomposition of the growth of sectoral TFP per worker, 2020-2022



Source of raw data: PSA.

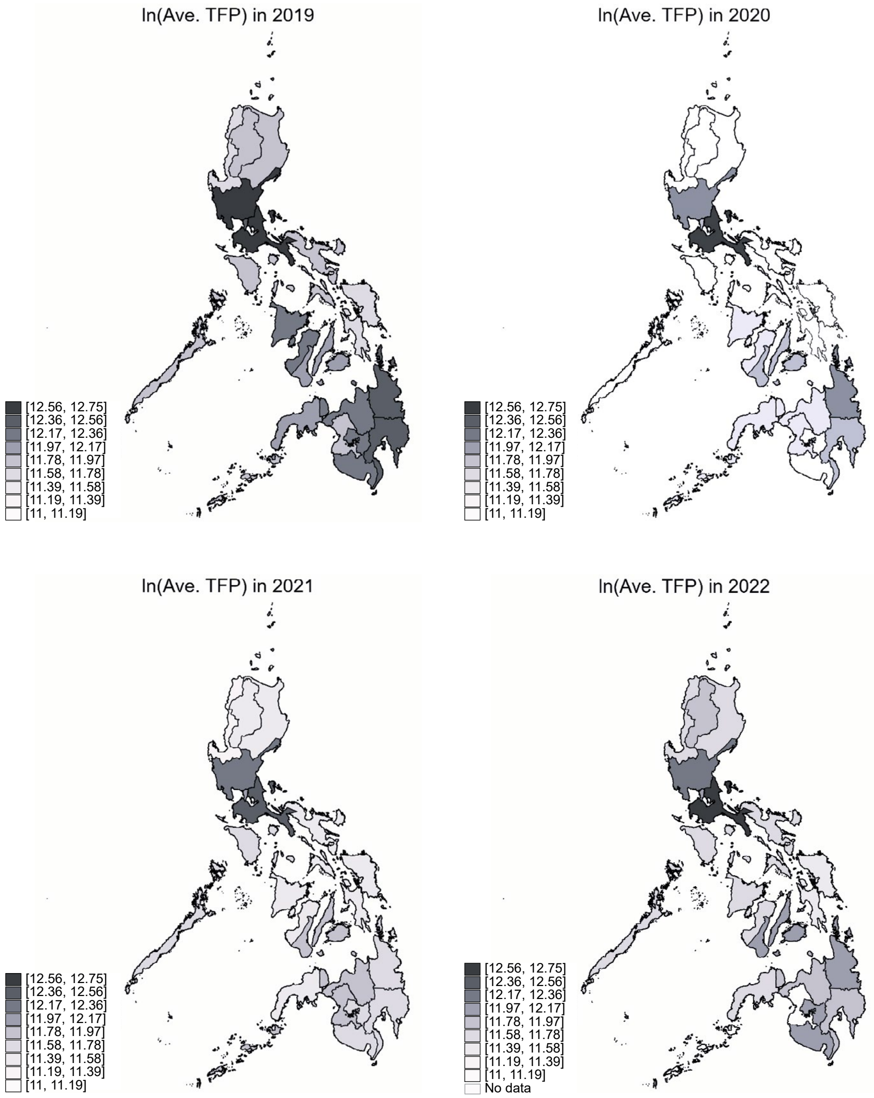
Two-Digit PSIC codes: 10 - Food Products, 11 - Beverages, 12 - Tobacco Products, 13 - Textiles, 14 - Wearing Apparel, 15 - Leather and Related Products, 16 - Wood and Related Products (excluding Furniture), 17 - Paper and Paper Products, 18 - Printing and Reproduction of Recorded Media, 19 - Coke and Refined Petroleum Products, 20 - Chemicals and Chemical Products, 21 - Basic Pharmaceutical Products and Pharmaceutical Preparations, 22 - Rubber and Plastic Products, 23 - Other Non-Metallic Mineral Products, 24 - Basic Metals, 25 - Fabricated Metal Products, except Machinery and Equipment, 26 - Computer, Electronic and Optical Products, 27 - Electrical Equipment, 28 - Machinery and Equipment, nec, 29 - Motor Vehicles, Trailers and Semi-Trailers, 30 - Other Transport Equipment, 31 - Furniture, 32 - Other Manufacturing, 33 - Repair and Installation of Machinery and Equipment

Figure 6 shows the variations in manufacturing TFP across regions and across time from 2019 to 2022. The color intensity of the maps noticeably dimmed in Region 3 (Central Luzon) and the National Capital Region (NCR) between 2019 and 2020, suggesting that productivity in these highly industrialized and export-oriented regions was heavily affected by pandemic shocks to supply chains and foreign demand. For instance, ADB [2020] reported that firms, especially in NCR, were heavily burdened by bottlenecks in customs processes and logistics services.[6] Nevertheless, manufacturing in the rest of the country also experienced significant productivity losses in 2020, especially in Region 4B (Mimaropa), Region 5 (Bicol), and Region 7 (Western Visayas). Protracted lockdown-induced disruptions and policy uncertainties caused the continued decline of productivity

[6] In China, Huang et al. [2022] found that COVID-19 negatively affected TFP growth in cities more than in rural areas. Excessively stringent containment measures such as lockdowns dampened productivity in urban areas where economic activities rely heavily on interconnected supply chains and physical mobility. According to the World Bank [2022], Philippine firms in urban areas, where most manufacturers are located, also faced higher operating costs and heavier burden of compliance to stricter lockdown measures.

in most regions in 2021, especially Region 4A (Calabarzon), which noticeably dimmed compared to 2020. By the end of 2022, Calabarzon was already close to returning to its 2019 average productivity, while other regions were relatively slower to recover.

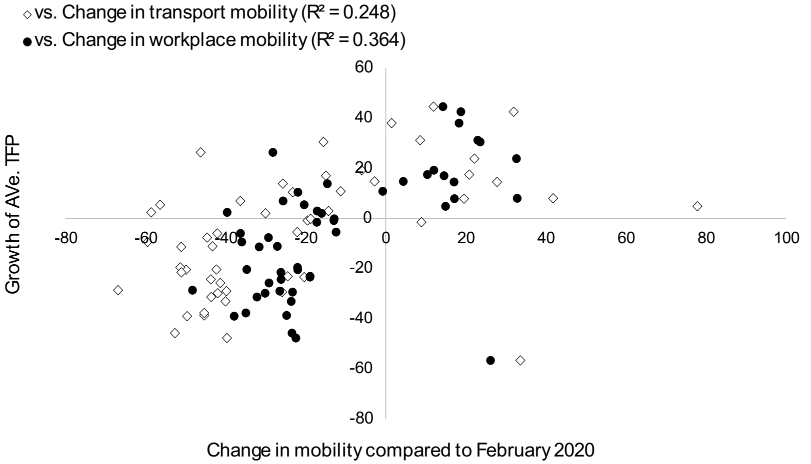
FIGURE 6. Average manufacturing TFP by region, 2019-2022



Sources of raw data: PSA and National Mapping and Resource Information Authority (NAMRIA).

Figure 7 shows that the regional variations in TFP dynamics is positively associated with transport and workplace mobility. This suggests that average TFP declined in regions that experienced significant loss of transport and workplace mobility relative to the pre-pandemic baseline in February 2020.

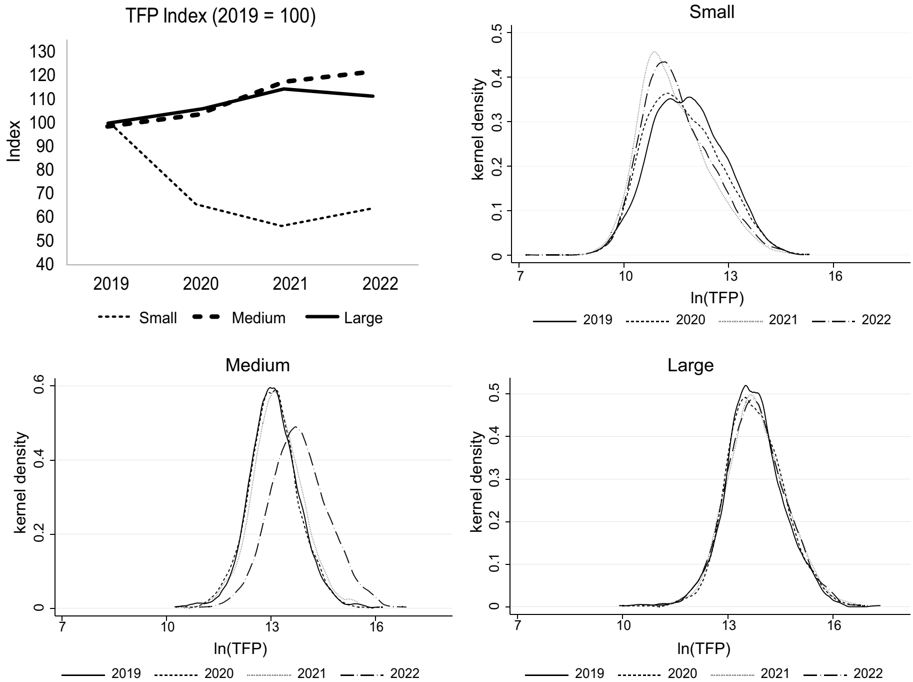
FIGURE 7. Growth of average TFP per region vs. average change in mobility, 2020-2022



Sources of raw data: PSA and Google COVID-19 Community Mobility Reports.

Figure 8 illustrates the TFP evolution of small, medium-sized, and large manufacturers from 2019 to 2022. The top left panel shows that productivity growth in medium and large manufacturers slowed down in 2020, while small firms endured a 34.72 percent TFP decline. Their post-pandemic recovery markedly diverged. The average TFP of large firms inched up in 2021, but fell by 2.44 percent in 2022. In contrast, the average productivity of SMEs contracted further by 12.38 percent in 2021, before recovering by 13.75 percent in 2022. The kernel distributions confirm this divergence. For small manufacturers, the distribution of TFP increased in dispersion and shifted leftward from 2019 to 2020. This suggests that the adverse productivity impact of the pandemic was more heavily felt by microenterprises. From 2020 to 2021, the distribution further moved leftward, with more small firms concentrating in a lower mean. Despite the rightward shift after 2021, the TFP distribution of small manufacturers in 2022 remained stochastically dominated by its pre-pandemic position. Medium-sized manufacturers seem more resilient than small and large firms, with their TFP distribution in 2020 and 2021 virtually unchanged from the 2019 position. By 2022, their TFP distribution already stochastically dominated the pre-pandemic position. The TFP distribution of large firms does not show significant movements between 2019 to 2022, suggesting that the productivity growth of this group slowed despite being robust during the pandemic.

FIGURE 8. Evolution of manufacturing TFP by size, 2019-2022



Source of raw data: PSA.

4. Regression analysis and KOB decomposition

Table 4 summarizes the TFP regression results based on Equation 2. Table 5 shows the estimates for SMEs only. Note that each covariate is tested individually for exogeneity using two-stage, least squares regressions, with the lagged explanatory variable used as instrument (see Appendix 4). The results do not point to any serious endogeneity issue at five percent, justifying the contemporaneous model specification in Equation 2. We reported FE rather than RE estimates based on the results of the Hausman tests. Column 5 summarizes the "naïve" FE regression results using the entire unbalanced sample. However, we caution that these estimates have not been fully adjusted for potential selection bias due to computational limitations in addressing the issue when using panel data. As partial robustness checks, we compared the results to the Heckman regression estimates using the pooled dataset (column 2) and the restricted FE regression results using the balanced panel of firms that consistently appeared in the sample from 2019 to 2020 (column 3). While the Heckman and FE estimates are not directly comparable, the Heckman regressions support the statistically significant results in the FE models. The magnitudes and significance of the FE estimates using the balanced and unbalanced datasets are broadly consistent, suggesting that the latter results are not purely driven by attrition of inferior firms and/or selfselection of highly productive manufacturers. The estimates in columns 4 and 5 are also close, suggesting that the addition of conservatively defined dummy variables do not distort the coefficients of the continuous variables (see Appendix 1 for the variable descriptions). Formal FE Heckman estimates for panel data were not obtained due to computational limitations. Nevertheless, column 6 reports the estimates after controlling for the inverse Mills ratio to partly correct for the potential selection bias.

For the entire sample, columns 5 and 6 show that age (ln), total hours worked (ln), average compensation (ln), and tangible investment have positive and significant relationships with ln*TFP*. We used total hours worked to proxy for the retained capacity of firms to operate amidst a highly uncertain business and policy environment caused by lockdowns, supply chain disruptions, and economic hibernation.[7] Adjusting work hours was one of the key strategies adopted by manufacturers to optimize their limited manpower amidst government-mandated suspensions of operations. This implies that during the pandemic, productivity was likely driven by how well manufacturers were able to remain operational even with minimal new innovation and investment activities.[8] In particular, an increase in total working hours by ten percent is matched by a 0.83 percent increase in expected TFP, *ceteris paribus*. This suggests that efficient labor utilization, despite labor productivity losses due to layoffs, sickness, mobility restrictions, and reduced capacity remained a key contributor to TFP growth during the pandemic. This may be expected given that among the covariates, total working hours is relatively variable which firms can flexibly adjust in the face of adverse shocks. This is consistent with the argument of Nadiri and Rosen [1969] that in the face of demand shocks, firms quickly adjust labor utilization rates though capital is inflexible in the short run. The World Bank's [2020; 2021] COVID-19 surveys also documented labor adjustments as the prevalent type of response adopted by Philippine businesses during the pandemic, while technological investments and digital solutions were less common.

Since TFP is a measure of how production can expand without having to increase labor and capital inputs, column 6 indicates that manufacturers with broader experience (as proxied by age) and more skilled human capital were better able to compensate for the lost capacity induced by lockdowns. According to column 6, a unit change in ln of age is associated with a 0.124 increase in ln*TFP*, holding other factors constant. We follow Vu et al.[2025] by using compensation per worker (ln) as proxy for human capital at the firm level, since higher wages strongly correlate with workers' skill level. All other factors equal, column 6 suggests that a ten-percent increase in average compensation is associated with at least 1.26 percent increase in average TFP. Across models, human capital consistently posted one of the largest average marginal effects, indicating its core relevance in driving productivity in

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[7] We thank the first reviewer for this suggestion.

[8] In the UK, Bloom et al. [2022] documented that TFP dropped by 5 percent between 2020 and 2021 due to reduced capacity utilization and higher input costs.

Philippine manufacturing during the pandemic. This implies that manufacturers with the most skilled workforce were better able to manage the disruptions caused by COVID-19. This result is broadly consistent with the productivity literature which identifies education, skills development, and training as important determinants of both innovation and productivity.

Lastly, columns 5 and 6 suggest that capital deepening has a robust positive and significant relationship with productivity growth during the pandemic. Controlling for other factors, manufacturers with investment in tangible assets also enjoyed at least 0.036 percent premium in average TFP. This partly reflects efforts of manufacturers to adjust their production in the context of limited mobility of workers and reduced production capacity in factories. In the ASPBI, investment in tangible assets aggregates capital spending on machinery and equipment, which includes ICT (e.g., computer and peripherals, telecommunications equipment), specialized industrial machinery, general industrial machinery and equipment (e.g., air conditioning and refrigeration equipment, pumps and compressor, power generating equipment), and other machinery and equipment (e.g., photographic equipment and optical goods). This suggests that capital-intensive manufacturers possibly responded to lockdowns, social distancing, and mobility restrictions partly through digital solutions, automation, and labor-saving technologies.

Other factors such as foreign ownership, importing, and exporting activities are significant in the pooled Heckman regression but not in the FE model. This means that despite significant cross-sectional heterogeneity, none of these covariates strongly affected the within-firm TFP changes across time. Interestingly, column 6 indicates that the significance of access to finance and R&D spending in column 5 is not robust. This suggests that the productivity effect detected in column 5 may have been driven by the non-random sample selection of firms with the said characteristics. For instance, financially-connected and R&D-intensive manufacturers have a higher chance of surviving the pandemic and being included in the sample. Therefore, the initial significance of financial access and R&D spending may only be relevant for these firms. For instance, a related survey of 454 firms in Central Luzon, Calabarzon, Central Visayas, and NCR found that businesses with large R&D investment before the pandemic were more resilient [ITC 2020]. Only 60 percent of firms with high R&D spending in 2019 reported to have been strongly affected by the pandemic. In contrast, 83 percent of companies with little pre-pandemic innovative activities were severely hit in 2020. R&D activities drive technological change within the firm, which can cause improvements in process efficiency, product diversification and quality, and overall productivity. In addition to the direct effects of R&D, ITC [2020] also highlighted that innovativeness signals a firm's adaptability and internal capacity to leverage its resources to deal with shocks and emerging market trends. This agility allowed some companies (e.g., San Miguel Corporation, Gouache, and Proctor & Gamble) to temporarily repurpose their processes to produce essential goods such as medical-grade and cloth face masks, alcohol and hand sanitizers, testing kits, personalized protective equipment, and other health-related products.

The dummy for intangible assets is weakly significant at 10 percent in column 6, reflecting generally limited investment of Philippine manufacturers on computer software and databases. Put differently, the slow post-pandemic TFP recovery of manufacturers, especially SMEs, may be partly driven by their lack of intangible technological assets which are vital for creating digital solutions to the disruptions caused by COVID-19. However, this may also mean that investment in intangible assets stagnated during and after the pandemic as resources were diverted to flexible resources (i.e., new equipment, training, and re-skilling) that can generate more immediate impact on raising revenues. Figure 2 suggests that this result was mainly driven by SMEs, given that their technological investment stalled after the pandemic.

Columns 5 and 6 of Table 5 show that efficient labor utilization and human capital are the only robust covariates of SMEs' productivity during the pandemic, suggesting that labor is the primary resource of smaller manufacturers. The dummy for tangible investment is not significant in column 6 of Table 5, suggesting that the productivity gains associated with investment in tangible assets are more relevant for large firms than for SMEs. This is intuitive given that these resources are naturally associated with-large scale manufacturing. The dummy variables for access to finance and positive R&D spending are also insignificant for SMEs. The limited productivity effect of financial access among SMEs aligns with the observation that many small businesses relied more on liquidation of assets, non-bank and informal lenders, and loans from family and friends [World Bank 2020, 2021]. In contrast, large corporations have access to a wider range of financing options, including borrowing from headquarters and partner firms, as well as equity financing. Similar to the full sample, the R&D dummy became insignificant for the productivity of SMEs after controlling for potential selection bias. This indicates that the initial positive productivity effect found in column 5 of Table 5 may be traced to non-random selection into R&D activities, driven by underlying characteristics such as superior managerial capability, stronger financial resources, or a culture of innovativeness. For SMEs, the dummy for intangible assets is also weakly significant at 10 percent in column 6, suggesting limited SME investment in these technologies despite their potential productivity-enhancing effect. Despite being highly significant in column 6 of Table 4, government subsidy is significant only at 10 percent in column 6 of Table 5, consistent with the World Bank's [2022] observation that smaller firms lacked awareness about public support programs, while actual uptake was discouraged by complex requirements and administrative hurdles. Larger firms benefited from these programs more than SMEs.[9]

[9] Various Philippine government agencies extended programs to address the financing needs of SMEs during the pandemic, such as the 60-billion-peso MSME Credit Guarantee Program of the Philippine Guarantee Corporation, the one-billion-peso loan facility of the Small Business Corporation, and the central bank's proactive measures to encourage commercial banks to provide more lending to SMEs [ADB 2020].

TABLE 4. TFP regressions for Philippine manufacturing, 2019-2022

	Heckman (Pooled Data)	Fixed Effects (Balanced Panel)	Fixed Effects (Unbalanced Panel)		
Foreign ownership (%)	-0.001*** (0.000)	-0.001 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.000)
Age (ln)	0.073*** (0.014)	0.051* (0.028)	0.042* (0.022)	0.040* (0.022)	0.124*** (0.044)
Total hours worked (ln)	0.276*** (0.009)	0.090*** (0.020)	0.083*** (0.011)	0.083*** (0.011)	0.083*** (0.021)
Average compensation (ln)	0.350*** (0.011)	0.145*** (0.018)	0.138*** (0.013)	0.133*** (0.012)	0.126*** (0.019)
Capacity utilization rate (%)	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
Importer only (dummy)	0.129*** (0.034)	-0.027 (0.081)		-0.017 (0.054)	0.064 (0.088)
Exporter only (dummy)	0.115*** (0.032)	0.067 (0.053)		0.063 (0.045)	0.067 (0.068)
Importer and exporter (dummy)	0.061** (0.029)	-0.042 (0.086)		-0.017 (0.058)	0.017 (0.096)
R&D spending (dummy)	0.007 (0.029)	0.047** (0.024)		0.056*** (0.020)	0.026 (0.027)
Access to finance (dummy)	0.055** (0.022)	0.028 (0.024)		0.040** (0.020)	0.026 (0.027)
Tangible investment (dummy)	0.101*** (0.021)	0.045*** (0.016)		0.053*** (0.013)	0.036** (0.017)
Intangible investment (dummy)	0.066 (0.042)	0.039 (0.029)		0.023 (0.025)	0.049* (0.029)
Government subsidy (dummy)	-0.052 (0.060)	0.121* (0.063)		0.065 (0.045)	0.148** (0.069)
Inverse Mills ratio	Yes	No	No	No	Yes
Number of observations	13,349	3,515	13,349	13,349	4,534
Within R^2		0.122	0.102	0.111	0.100

Source of raw data: PSA
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
The dependent variable is ln*TFP*. All regressions include controls for size, sector (at the three-digit PSIC level), region, and year. All explanatory variables passed the test for exogeneity using the two-stage least squares, with their respective lagged values as instruments. Numbers in parentheses are cluster-robust standard errors, with Establishment Control Number (ECN) as the cluster variable. For the Heckman regression, the selection equation models the probability of being observed in the next period based on foreign ownership, age (ln), total hours worked (ln), average compensation (ln), capacity utilization, total employees (ln), region, sector (at the three-digit PSIC level), and year. Consistent with the Heckman methodology, column 6 was estimated using only the non-censored observations in the selection equation. The inverse Mills ratios are significant in columns 2 and 6. The Hausman tests suggest that the FE regressions are more appropriate for the data than the RE regressions.

TABLE 5. TFP regressions for Philippine manufacturing SMEs, 2019-2022

	Heckman (Pooled Data)	Fixed Effects (Balanced Panel)	Fixed Effects (Unbalanced Panel)		
Foreign ownership (%)	-0.002***	0.000	0.000	0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Age (ln)	0.051***	0.025	0.025	0.026	0.123*
	(0.017)	(0.035)	(0.026)	(0.026)	(0.064)
Total hours worked (ln)	0.257***	0.103***	0.083***	0.082***	0.103***
	(0.012)	(0.028)	(0.015)	(0.015)	(0.029)
Average compensation (ln)	0.335***	0.154***	0.131***	0.127***	0.115***
	(0.014)	(0.025)	(0.015)	(0.015)	(0.026)
Capacity utilization rate (%)	0.000	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Importer only (dummy)	0.167***	0.049		0.036	0.202*
	(0.043)	(0.107)		(0.065)	(0.111)
Exporter only (dummy)	0.107***	-0.003		0.090	0.045
	(0.040)	(0.083)		(0.062)	(0.113)
Importer and exporter	0.113***	-0.093		0.005	0.044
(dummy)	(0.039)	(0.119)		(0.075)	(0.116)
R&D spending (dummy)	0.008	0.055		0.093***	0.040
	(0.040)	(0.034)		(0.026)	(0.040)
Access to finance (dummy)	0.070**	0.004		0.024	0.007
	(0.028)	(0.035)		(0.026)	(0.039)
Tangible investment	0.075***	0.023		0.041**	0.004
(dummy)	(0.028)	(0.022)		(0.017)	(0.026)
Intangible investment	0.020	0.051		-0.002	0.088*
(dummy)	(0.067)	(0.045)		(0.036)	(0.051)
Government subsidy	-0.146*	0.155*		0.065	0.174*
(dummy)	(0.083)	(0.089)		(0.055)	(0.092)
Inverse Mills ratio	Yes	No	No	No	Yes
Number of observations	10,708	1,977	10,708	10,708	2,963
Within R^2		0.115	0.089	0.096	0.091

Source of raw data: PSA.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
The dependent variable is ln*TFP*. All regressions include controls for size, sector (at the three-digit PSIC level), region, and year. All explanatory variables passed the test for exogeneity using the two-stage least squares, with their respective lagged values as instruments. Numbers in parentheses are cluster-robust standard errors, with Establishment Control Number (ECN) as the cluster variable. For the Heckman regression, the selection equation models the probability of being observed in the next period based on foreign ownership, age (ln), total hours worked (ln), average compensation (ln), capacity utilization, total employees (ln), region, sector (at the three-digit PSIC level), and year. Consistent with the Heckman methodology, column 6 was estimated using only the non-censored observations in the selection equation. The inverse Mills ratios are significant in columns 2 and 6. The Hausman tests suggest that the FE regressions are more appropriate for the data than the RE regressions.

The preceding discussions showed that the revenues, employment, and productivity of SMEs and large manufacturers have diverged markedly after the pandemic. Large firms quickly rebounded from the temporary setback in 2020, while SMEs struggled to return to pre-pandemic level. However, a closer look at SMEs suggests that the productivity of small and medium-sized manufacturers is also drifting apart. Figure 8 shows that medium-sized firms have already surpassed their pre-pandemic productivity, while the performance of small firms stalled. This phenomenon has important implications on policy given that most government programs and interventions target the two categories as one big group. However, significant distinctions suggest that the two have size-specific needs that should be treated differently. We further investigated this divergence using the KOB decomposition method described in Section 2.3. At the onset, we justify the use of KOB decomposition based on sufficient overlaps in the kernel densities of small and medium-sized firms across the covariates used (see Appendix 5). Yet, Figure 8 shows that their respective TFP distributions markedly diverge. The results summarized in Table 6 confirm that the average ln*TFP* gap between small and medium-sized manufacturers have widened significantly from 1.936 in 2019 to 2.482 in 2022. To be at par with medium-sized manufacturers, small producers needed more endowments in 2021 and 2022 compared to what was required in 2019 and 2020. This is consistent with the divergence argument, which implies a further marginalization of SMEs' contribution in manufacturing TFP growth given that large firms are close to regaining their pre-pandemic productivity.

The estimates point to differences in endowments and time-constant or persistent underlying traits as the biggest sources of ln*TFP* gap between small and medium-sized manufacturers. The structural and interaction effects are insignificant at five percent, indicating the broad similarity of the production technologies of the two groups. The *EE* alone accounted for 15.44 percent of the gap in 2022, up from 12.72 percent in 2019. This was mainly traced to large differences in foreign ownership, total hours worked, and capacity utilization. Their limited resources to respond to the disruptions suggest that the TFP slowdown of small firms during and after the pandemic was the natural consequence of their size. The *EE* estimate in 2019 indicates that the average ln*TFP* of small firms would have increased by 0.246 if they had the same resources as medium-sized manufacturers. This endowment gap further widened during and after the pandemic—from 0.266 in 2020 to 0.375 and 0.383 in 2021 and 2022, respectively. This steady rise highlights the role of differential resource access, which exacerbated during the pandemic, in the growing productivity gap between the two groups. This is consistent with the World Bank [2022] survey suggesting that two years after the Great Lockdown, smaller Philippine firms remained disproportionately burdened by weak cash flows and ongoing arrears *vis-à-vis* limited access to formal finance, cautious hiring due to operational constraints, and inadequate capacity and infrastructure for digital solutions.

TABLE 6. KOB decomposition of the ln*TFP* gap between small and medium-sized manufacturers, 2019-2022

	2019	2020	2021	2022
EE	0.246***	0.266***	0.375***	0.383***
	(0.052)	(0.057)	(0.065)	(0.059)
	[12.722]	[12.745]	[14.761]	[15.442]
SE	0.178*	0.169*	0.277*	0.142
	(0.082)	(0.078)	(0.132)	(0.117)
	[9.203]	[8.083]	[10.900]	[5.724]
IE	-0.069	-0.085	-0.225	-0.092
	(0.078)	(0.077)	(0.128)	(0.116)
	[-3.553]	[-4.059]	[-8.848]	[-3.699]
UE	1.580***	1.738***	2.114***	2.049***
	(0.066)	(0.063)	(0.072)	(0.065)
	[81.628]	[83.231]	[83.188]	[82.533]
Total	1.936***	2.088***	2.542***	2.482***
	(0.040)	(0.040)	(0.038)	(0.032)

Source of raw data: PSA.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
EE – endowment effect, *SE* – structural effect, *IE* – interaction effect, *UE* – effect of unobservable traits
Due to the computational limitations, regional fixed effects only control for major island groups (i.e., Visayas and Mindanao, with Luzon as the baseline), while sectoral fixed effects only control for broad groupings by level of technology (i.e., medium-low tech, medium-high tech, and high tech, with low tech as the baseline). Numbers in parentheses are bootstrapped standard errors. Number in square brackets are percentage shares in total ln*TFP* gap per year.

Time-constant unobservable factors are the dominant source of productivity differences between small and medium-sized manufacturers. This suggests that medium-sized firms are not simply scaled up versions of small firms. Their inherent heterogeneity in managerial quality, organizational structures, and innovation culture, may have contributed to the documented pre-pandemic ln*TFP* gap, which further widened after 2020. Locational disadvantages may have also exacerbated small firms' limited access to resources, especially in sectors or regions that are distant from public goods and markets. ITC [2020] also suggest that networks and relationships with clients and suppliers matter. These connections provide vital information about market trends, regulations, emerging business practices, and technologies which manufacturers can use to upgrade their operations. ITC [2020] observed that producers connected to their buyers, especially large companies, are more likely to innovate and have a business plan. However, in the Philippines, smaller firms have low tendency to form strong connections to clients, on top of their already limited forward and backward linkages with large businesses [ITC 2020].

TABLE 7. KOB decomposition of the change in the ln*TFP* gap between small and medium-sized manufacturers, 2020-2022

	2020	2021	2022
ΔEE	0.031	0.089**	0.059
	(0.026)	(0.032)	(0.030)
	[20.412]	[14.613]	[10.772]
ΔSE	-0.025	-0.036	0.011
	(0.030)	(0.035)	(0.035)
	[-16.384]	[-5.944]	[1.960]
ΔIE	-0.012	0.019	0.008
	(0.013)	(0.017)	(0.019)
	[-7.602]	[3.161]	[1.531]
ΔUE	0.158***	0.534***	0.469***
	(0.044)	(0.049)	(0.050)
	[103.574]	[88.171]	[85.738]
Total	0.153***	0.606***	0.546***
	(0.043)	(0.046)	(0.045)

Source of raw data: PSA.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
EE – endowment effect, *SE* – structural effect, *IE* – interaction effect, *UE* – effect of unobservable traits
Due the computational limitations, regional fixed effects only control for major island groups (i.e., Visayas and Mindanao, with Luzon as the baseline), while sectoral fixed effects only control for broad groupings by level of technology (i.e., medium-low tech, medium-high tech, and high tech, with low tech as the baseline). Numbers in parentheses are bootstrapped standard errors. Number in square brackets are percentage shares in the change in ln*TFP* gap per year.

Finally, Table 7 summarizes the results of the decomposition of change based on Equation 5. The estimates confirm that the rate of change in endowment differences between small and medium-sized manufacturers accelerated in 2021, which contributed to the wider overall ln*TFP* gap between the two groups. Another interesting observation is the relatively large share of ΔEE in 2020, suggesting that small firms were disproportionately burdened by COVID-19 disruptions early on due to their limited resources. Small firms' weak performance in 2021 and 2022 indicates that they still haven't fully recovered from this shock two years after the pandemic. The rate of change in the TFP differential due to persistent unobservable traits also accelerated from 0.158 in 2020 to 0.534 in 2021 and 0.469 in 2022, emphasizing the relevance of inherent time-invariant traits such as managerial quality, organizational culture, location, and networking ability in dealing with adverse shocks. Therefore, addressing the increasing productivity spread between small and medium-sized manufacturers should focus on interventions that upgrade smaller firms' core competencies and improve their access to resources. To a certain extent, this will involve easing the regulatory burden implemented during the pandemic which created a harsh business environment that disproportionately affected SMEs. In contrast, ΔSE and ΔIE are consistently insignificant across years. This may be explained by the relatively stable coefficients of the two groups of manufacturers, given that production structures are not expected to change drastically in the short run.

5. Concluding remarks

This paper used 2019 to 2022 data from the ASPBI to obtain updated estimates of establishment-level TFP and construct stylized facts about the post-pandemic productivity dynamics of Philippine manufacturers, especially SMEs. The results confirm the severe but highly heterogenous productivity impact of the pandemic across sectors and regions. Low-tech sectors experienced bigger TFP declines compared to high-tech sectors. Manufacturing productivity in major industrial and export-oriented regions were badly hit by pandemic-induced supply chain shocks partly due to mobility restrictions, but recovery was highly uneven. The results also reveal the divergent post-pandemic TFP dynamics between SMEs and large manufacturers, with the latter experiencing large productivity losses in 2020 but gradually recovering in 2021. Medium-sized manufacturers were surprisingly resilient, with their TFP in 2022 already surpassing the 2019 benchmark. Small manufacturers, especially microenterprises, not only endured the biggest productivity loss in 2020 but also struggled to return to pre-pandemic level.

The FE regressions suggest that Philippine manufacturing TFP during the pandemic was primarily driven by total hours worked, human capital (proxied by average compensation), experience (proxied by age), and tangible investment. This suggests that highly productive manufacturers compensated their reduced production capacity through efficient labor utilization, skilled manpower, and capital deepening, which enabled agile business adjustments amidst restricted mobility of workers, limited operations in factories, supply chain disruptions, and negative demand shocks. However, the productivity premia from R&D spending, access to finance, and intangible investment are not robust. Other factors such as foreign ownership, capacity utilization, and trading activity were insignificant in the FE model that accounted for within-firm TFP variations across time.

A closer look at SMEs revealed the deviant post-pandemic TFP recovery of small and medium-sized firms. Further decomposition of this divergent pattern suggests that differences in endowments and persistent underlying traits are the biggest sources of the productivity gap between small and medium-sized manufacturers, while the structural and interaction effects are insignificant. The endowment effect was mainly driven by large gaps in foreign ownership, total hours worked, and capacity utilization, suggesting that the slow post-pandemic TFP recovery of small firms was naturally constrained by their size. The large productivity gap traced to time-invariant unobservable characteristics emphasize the relevance of persistent underlying traits such as managerial quality, organizational culture, location, and networking ability in dealing with adverse shocks. Decomposition by year further showed that the endowment and unobserved effects increased from 2019 to 2022, which implies that to catch up with medium-sized manufacturers, small firms needed more resources in 2022 compared to the requirement in previous years. Decomposition of change also indicated that the change in the productivity gap due to endowment and unobserved fixed effects accelerated, which resulted in a TFP differential in 2022 that was wider than in 2020. The productivity divergence between small and medium-sized manufacturers calls for a careful reassessment of blanket programs that do not distinguish between the two groups. Poorly-targeted interventions may further marginalize SMEs' contribution in manufacturing TFP growth given that large firms are close to regaining their pre-pandemic productivity.

The empirical results broadly align with the kinds of support requested by firms from the government during and after the pandemic (ADB [2020]; UNIDO [2020]; World Bank [2020; 2021; 2022]). For instance, UNIDO [2020] and World Bank [2020] documented strong and urgent demand for government support for liquidity-improving measures (e.g., cash transfers, new loans with lower interest rates, deferral of loan payments, credit mediation and refinancing, loan restructuring), wage subsidies, flexible work arrangements and labor policies, health- and mobility-improving policies, digital skills training, and digital technology adoption during the early phase of the lockdowns. ADB [2020] also noted demand for support for rehiring and re-skilling displaced workers, capacity building for e-commerce and remote operations, and support for investment in digital infrastructure. By 2021, firms were requesting for free and preferential access of their employees to vaccines when they became available [World Bank 2022]. Clearly, these desired government interventions are justified by the empirical results which suggest that firms, especially SMEs, needed to improve their production workforce, capacity utilization, access to finance, and investment in digital assets in order to boost their post-pandemic productivity. However, the aforementioned reports also observed low awareness and actual uptake of the support programs rolled out by the government during the pandemic. Moreover, larger firms benefited more than SMEs. An important lesson here is that in times of adverse shocks, there is value in implementing frequent business pulse surveys that can provide an accurate sense of the situation and needs of establishments, especially SMEs. However, while timely policy support matters for the survival of businesses, information dissemination, proper targeting, and efficient implementation are also important to ensure that the assistance will reach those who actually need it.

The generally slow post-pandemic recovery of manufacturing TFP, which was largely driven by the lagging productivity of small firms, deserves more effective policy interventions due to its non-trivial implications on welfare and national development objectives. First, there is empirical evidence that manufacturing TFP directly influences economic growth as well as capital and labor productivity

[Jia et al. 2020]. Second, SMEs are important generators of new formal jobs in the developing world [Ayyagari et al. 2014]. The fact that small firms struggled to return to their pre-pandemic revenue, employment, and productivity levels will not only result in welfare losses but will also exacerbate the scarring effect of COVID-19. For a country that is aspiring to upgrade to the status of a rising industrial powerhouse, addressing these divergent productivity trends should be part of the post-pandemic growth strategy.

The METTRICS dataset used in this paper has unlocked new opportunities to study the post-pandemic experience of Philippine establishments. Future research can leverage its granularity to examine how regional and sectoral variations in lockdown policies shaped firm trajectories, highlighting differences in resilience across industries and locations.[10] By linking METTRICS with aggregate indicators such as mobility or local policy variables, causal analysis could further reveal the mechanisms driving recovery or stagnation of certain groups of firms. For instance, could unequal access to specific support programs during the pandemic have led to the productivity divergence between small and medium firms? Extending the METTRICS backwards will allow richer analysis of other global shocks such as trade wars and financial crisis.

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Appendices

APPENDIX 1. Description of variables used

Variable	Unit of measurement	Description
Value added output	Pesos (in 2018 prices)	Gross output less intermediate input
Labor	Persons	Total number of persons employed
Capital	Pesos (in 2018 prices)	Depreciation-adjusted book value of buildings, transport equipment, and machinery and equipment
Intermediate inputs	Pesos (in 2018 prices)	Costs of raw materials, electricity, and fuel
Industry GDP deflator	Index	Ratio of nominal to real value of the industry component of gross domestic product
Foreign ownership	Percent	Capital participation of foreign investors
Age	Years	Number of years since start of operation
Hours worked	Hours	Total hours spend by production workers at work
Average compensation	Pesos (in 2018 prices)	Total compensation expense/total employees
Capacity utilization rate	Percent	Ratio of total output to the maximum capacity of the establishment
Exporter	Dummy	1 if the establishment reported positive exports
Importer	Dummy	1 if the establishment reported positive imports
R&D spending	Dummy	1 if the establishment reported positive R&D expense
Access to finance	Dummy	1 if the establishment reported positive interest income from financial assets
Tangible investment	Dummy	1 if the establishment reported capital expenditures on machinery and equipment
Intangible investment	Dummy	1 if the establishment reported capital expenditures on intangible non-produced assets, computer software and databases, and R&D
Government subsidy	Dummy	1 if the establishment reported to have received subsidy, grant, aid, or financial assistance from government

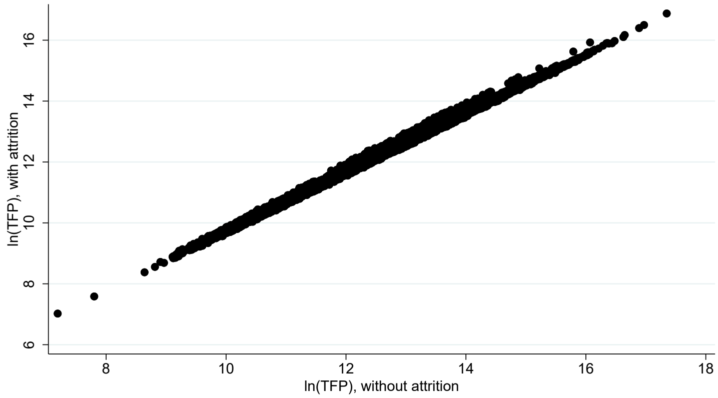
Note: All establishment-level variables are derived from the METTRICS dataset for 2019 to 2022.

APPENDIX 2. Summary statistics of variables used in the regressions

Variable		Mean	Std. dev.	Min	Max
TFP (ln)	overall	12.294	1.306	8.814	17.348
	between		1.244	8.814	16.964
	within		0.210	10.411	14.652
Foreign ownership (%)	overall	15.750	33.767	0	100
	between		27.861	0	100
	within		10.118	-59.225	90.750
Age (ln)	overall	2.654	0.905	0	5.130
	between		0.944	0	5.106
	within		0.191	-0.035	4.765
Hours worked (ln)	overall	11.156	2.027	0	17.891
	between		1.920	0	17.528
	within		0.354	3.690	15.221
Average compensation (ln)	overall	11.788	1.062	-0.693	17.860
	between		1.038	-0.693	17.340
	within		0.336	8.983	14.738
Capacity utilization rate	overall	74.571	19.013	1	100
	between		18.523	1	100
	within		8.599	8.571	122.071
Exporter (dummy)	overall	0.277	0.447	0	1
	between		0.384	0	1
	within		0.112	-0.473	1.027
Importer (dummy)	overall	0.246	0.431	0	1
	between		0.361	0	1
	within		0.060	-0.504	0.996
R&D spending (dummy)	overall	0.080	0.271	0	1
	between		0.209	0	1
	within		0.146	-0.670	0.830
Access to finance (dummy)	overall	0.317	0.465	0	1
	between		0.402	0	1
	within		0.174	-0.433	1.067
Tangible investment (dummy)	overall	0.246	0.431	0	1
	between		0.360	0	1
	within		0.223	-0.504	0.996
Intangible investment (dummy)	overall	0.033	0.180	0	1
	between		0.134	0	1
	within		0.104	-0.717	0.783
Government subsidy (dummy)	overall	0.016	0.126	0	1
	between		0.103	0	1
	within		0.072	-0.734	0.766

Source of raw data: PSA.
For all variables, N = 13349, n = 8453, T-bar = 1.579

APPENDIX 3. Scatter diagram of TFP estimates from the LP models with and without attrition



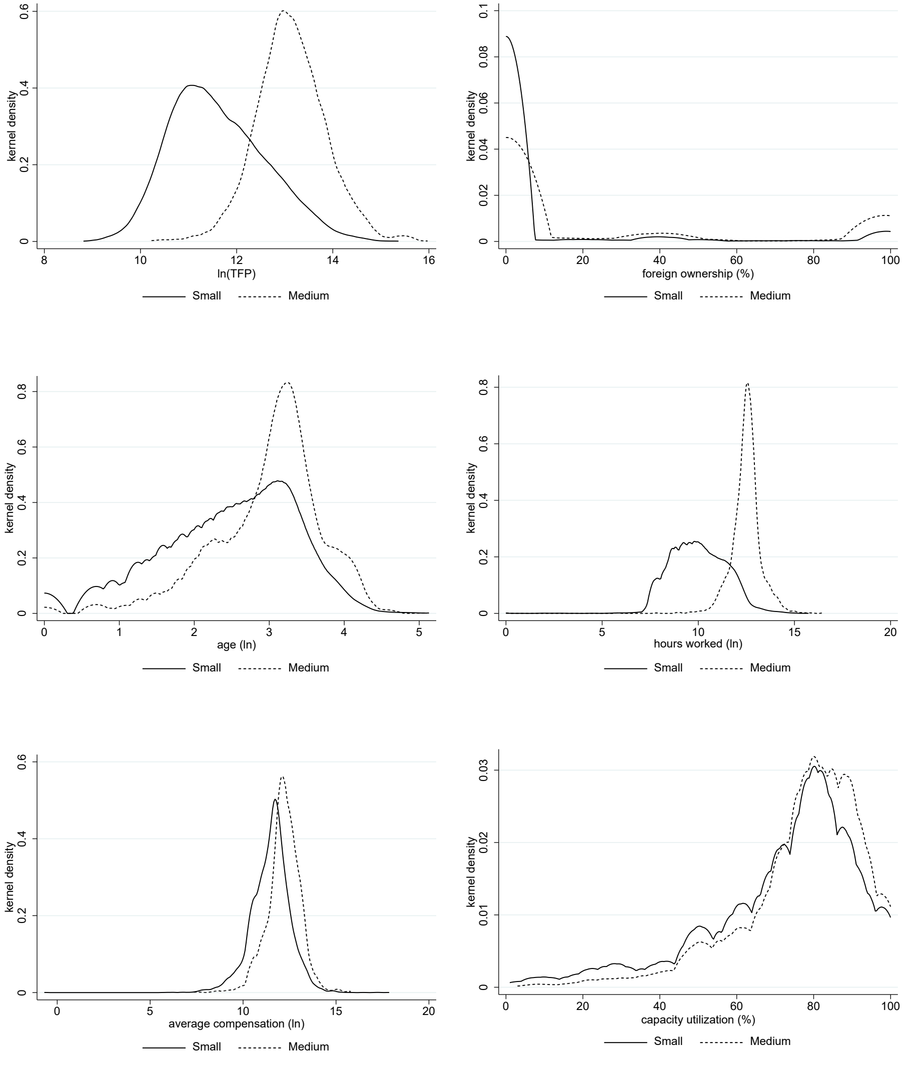
Source of raw data: PSA.

APPENDIX 4. Individual tests for weak instruments and exogeneity

	All manufacturers		SMEs	
	Cragg–Donald Wald *F*-statistic	**Endogeneity test χ^2**	**Cragg–Donald Wald *F*-statistic**	**Endogeneity test χ^2**
Foreign ownership (%)	56.270	1.289	27.436	0.377
Age (ln)	26.466	0.016	36.224	0.027
Total hours worked (ln)	71.419	0.001	43.215	1.820
Average compensation (ln)	71.191	0.339	14.768	0.332
Capacity utilization rate (%)	130.087	0.988	85.298	0.056
Exporter (dummy)	36.138	0.195	32.304	0.539
Importer (dummy)	38.792	0.120	18.117	0.766
R&D spending (dummy)	97.017	0.347	47.057	0.041
Access to finance (dummy)	122.778	0.025	71.081	0.461
Tangible investment (dummy)	181.896	0.174	82.216	0.196
Intangible investment (dummy)	195.924	0.850	144.764	0.015
Government subsidy (dummy)	147.021	0.396	90.992	0.274

• The Cragg–Donald Wald *F*-statistics are above the Stock and Yogo 10 percent maximal IV size critical value of 16.38, rejecting the null hypothesis of weak instruments. For average compensation (ln) in the SMEs subsample, the Cragg–Donald Wald F-statistic is greater than the 15 percent maximal IV size critical value of 8.96 and the Staigler-Stock threshold of 10.
• At 5 percent level of significance, the endogeneity test cannot reject the null hypothesis that the regressor being tested is exogenous.

APPENDIX 5. Kernel densities of small and medium-sized firms across various characteristics



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