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ADB Working Paper Series

**THE FATE OF JOB CREATION
IN THE PHILIPPINES AMID THE
AUTOMATION REVOLUTION:
A FIRM-LEVEL ANALYSIS**

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Abstract

Using the World Bank's Enterprise Survey for the Philippines, our analysis found that, on average, firms that deployed partial or full automation in their operations were more likely to hire more workers than fewer relative to their counterpart firms. These results suggest a net positive employment impact of automation, at least in the short run. The findings differ, however, by industries—net job creation is significant only among manufacturing firms. In contrast, we found that firms in the service industry have a higher likelihood of net job losses as they adopt partial or full automation. Indeed, there is an expectation that firms' decision to automate will cause labor market disruptions, which deserve immediate policy interventions. Human capital development, such as education and training, would be a critical policy lever to prevent the adverse effect of job displacement on the economic, social, and psychological well-being of individuals. The government should prepare workers to acquire the right set of skills and competencies, making them more flexible and able to fulfill new tasks amid further adoption of automation. Otherwise, the anxiety over the future loss of work will become a reality.

Keywords: automation, labor market disruptions, employment, Philippines

JEL Classification: J21, J23, J24

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1. INTRODUCTION

Technological advances create both economic opportunities and challenges. One such challenge is the anxiety that arises over the future of work (Innes and Morrison 2017). Productivity improvement from the use of computers and the deployment of robots may reduce the demand for labor to produce a good or deliver a service. The risk of automation, however, seems to pose a greater concern for jobs involving tasks that are repetitive, manual, and simple, which are more automatable than more diverse, cognitive, emotional, and complex tasks (Asian Development Bank 2018).

The literature on the impact of automation on labor has offered mixed views. Autor (2015) argued that, while automation generally intends to substitute manual labor, the demand for human workers to perform other tasks would also increase owing to machines producing output more quickly and cheaply. Bessen (2015) followed the same line of thought, noting the historical example of the automation of weaving in the US in the 19th century. The demand for weavers declined because of the increased productivity, but the downward adjustment of the price of cloth pushed the demand up, which in turn led to a greater demand for weavers. Others, however, have argued that disruptions from more advanced technologies, such as artificial intelligence, deep learning, the Internet of Things, and 3D printing, are likely to be wider in scope than the previous industrial revolutions. Ford (2015) explained that the broad-based adoption of technologies, such as computers and e-commerce, across all industries could be an indication of how widely the global corporate world could adopt new technologies, such as automation. This view was shared by Schwab (2016), noting the expectation that the disruptive effects of advanced technologies will be wide in scope and on a scale large enough to displace jobs.

The potential labor market implications of automation also apply in the context of developing economies while they remain at the initial stages of technological adoption. The World Bank (2016) estimated that a large proportion of occupations in developing economies, such as the People's Republic of China, India, and Ethiopia, will become automated. However, the possible displacement of these jobs will remain at bay due to the moderate pace of technological adoption and low labor costs in these areas. In Southeast Asia, labor-intensive jobs in electronics, automotive, textiles, and retail services are particularly at risk from automation (Chang, Rynhart, and Huynh 2016). Further, given their capacity to invest heavily in automation and artificial intelligence, multinational firms, often from advanced economies, may decide to relocate their production facilities to their home country or where their market is located, displacing workers from developing economies.

This paper narrows the scope and considers the case of the Philippines labor market. The country holds firmly onto employment creation to achieve the inclusive growth goal that the Philippine Development Plan 2017–2022 stipulated. However, the risk of automation, which could infiltrate the Philippines labor market just like any other labor market in the region, could equate to massive layoffs and potentially increase unemployment. While the country's manufacturing sector has been slow to adopt automation, with only three installed industrial robots for every 10,000 employees in 2016 (International Federation of Robotics 2018), it is apparent that the number of business process outsourcing firms deploying robotic process automation is growing amid observed productivity gains. The empirical analysis of the paper aims to evaluate the labor market disruptions of firm-level automation decisions and provide policy insights not only to manage potential adverse consequences but also to take advantage of some opportunities that will arise in the Philippines labor market.

This paper also contributes to the literature and the ongoing debate among academics, scholars, and policy makers on how further advances in technologies will disrupt the labor market. Much of the literature on this topic has dwelled heavily on estimating jobs at risk of automation by analyzing the automatability of the tasks involved, the pace and extent of adoption, and the ease of labor substitution, among others. An innovation of this paper lies in its evaluation of the issue through the lens of enterprises, which we believe could capture the interplay of the relevant labor demand and supply factors, including firms' technological capacity, the task composition of jobs, and workers' skills, among others.

Using the World Bank's Enterprise Survey for the Philippines, this paper attempts to understand generally how automation decisions change the hiring behavior of firms operating in the Philippines. The paper aims to determine whether firms that are more inclined to adopt new and advanced technologies are more likely to reduce human labor, particularly in low-skilled positions. Broadly, the results suggest that firms that have adopted partial or full automation to develop their new products or services, on average, are likely to hire more workers than their counterpart firms. Firms' decision to automate is associated with significant growth in the hiring of new workers, a scenario, based on the estimates, that is much more likely to occur than massive worker layoffs. Interestingly, the study finds that the greater propensity of firms to automate is associated with a larger proportion of the total full-time employment of unskilled workers. Despite the observations, these firms offer more formal training to their workers. The potential rise in the demand for unskilled workers who can handle non-routine manual tasks could explain such a finding. Last, the paper determines how increasing automation could benefit the female workforce in the Philippines.

The next section provides a general overview of the Philippine labor market as well as the pace of the automation revolution in the country. Section 3 explains the conceptual framework and the empirical approach that the analysis in this paper follows. Section 4 presents the empirical findings. Lastly, section 5 concludes and recommends policy directions concerning how the Philippines could take advantage of the economic opportunities and face the challenges that the automation revolution presents.

2. THE STATE OF WORK AND AUTOMATION IN THE PHILIPPINES

Will the automation revolution worsen the job prospects of the Filipino workforce? To answer this question, first we needed to examine the labor market structure of the Philippines as well as the propensity and pace of automation of firms operating in the Philippines.

Deriving from the January 2018 round of the Philippine Labor Force Survey that the Philippine Statistics Authority (2018) conducted, the Philippine labor force climbed nearly 5% to 44 million from 42 million during the same period in 2017. Of the total labor force, only 38% is female, and the participation rate for women remains low relative to that of their male counterparts. The number of employed persons increased even more, by 6.1%, causing the unemployment rate to drop to 5.3%. It is worth noting that male and female employment grew at a similar pace. Many of the gains in total employment, however, are attributable to the larger amount of part-time employment or those with fewer than 40 working hours per week; thus, underemployment remains a concern that the country should address.

By industry, the service sector remains the major source of employment in the country, more than a third of which is involved in retail and wholesale trade. The agriculture sector still accounts for more than a quarter of the total employed persons, despite its falling share of the total gross value added. The manufacturing and construction sectors also employ a large workforce, with their individual share of the total employment exceeding 8%. Another important employment contributor in the country is the business process outsourcing sector; estimates have indicated that it employs about 1 million workers. Based solely on the sectoral decomposition of employment, without considering the pace of automation adoption in these industries, the disruptions in the labor market in the Philippines could be massive. According to the McKinsey Global Institute (2017), the technical potential for automation of the sectors that generate most of the employment in the Philippines is considerably high.

We also intended to take a close look at the occupational make-up of the country's labor market. The January 2018 labor force survey showed that 27.6% of Filipino workers are involved in elementary occupations and perform simple and routine tasks using handheld tools and considerable physical effort. It is evident that the majority of the employment gains come from this occupation group. It is followed by those performing managerial roles (16.3%). There are also many service and sales workers (14.7%), skilled agricultural, fishery, and forestry workers (13.1%), craft and related trade workers (7.1%), and plant and machine operators and assemblers (6.4%). These occupations perform tasks that are easily automatable, classified as manual and routine. The call center jobs in the country also fall into this category despite the involvement of some cognitive tasks. Meanwhile, professionals and technicians performing technical and related tasks comprise only 9% of the total employment.

Aside from assessing the feasibility of partial and full automation of tasks and their application in broad sets of industries to determine how vulnerable the country's labor market will be in the age of automation, it is equally worthwhile to examine the issue from the perspective of enterprises. While there are tasks that are easily automatable, firms also consider the costs associated with upgraded or completely automated production. The economic feasibility of automation, having considered all the costs, such as capital, time, and effort, will influence and shape firms' decision regarding the adoption of automation (McKinsey Global Institute 2017).

Using the 2016 International Labour Office survey, Orozco (2017) found a low technology uptake among 575 surveyed enterprises in the Philippines. Of the total respondent firms, only 27% had upgraded their technology and an even lower 19% had spent money on research and development activities. When asked about the key reason for the low adoption, more than 30% of the respondents cited the high fixed capital cost involved in completing such activities. Compared with other surveyed Southeast Asian countries, such as Cambodia, Indonesia, Thailand, and Viet Nam, a smaller number of firms in the Philippines mentioned the lack of skilled operators as a major barrier to technology upgrading. Despite the low uptake, many firms in the Philippines perceive that technological advances would bring huge economic opportunities to their enterprise by 2025. This may reflect the enthusiasm of firms about deploying automation technologies soon that will have labor market implications in the country.

The labor impact of the automation revolution remains generally uncertain, but what is certain is that the Philippine labor market is a pool of medium- and high-skilled workers, which offers the opportunity and flexibility to face challenges once full-scale automation has taken place in the near future.

3. THEORETICAL FRAMEWORK

This study applied the theory of two-factor labor demand to understand firms' hiring decisions given their propensity to adopt automated processes. The framework guided us to derive an empirically tractable specification that could determine whether and to what extent automation affects the hiring decisions of firms operating in the Philippines.

Consider a firm with a production function, $Y = AF(L, K)$, and assume the conditions $F' > 0$, $F'' < 0$, and constant returns to scale. Firms maximize their profit, $\pi = F(L, K) - wL - rK$, where w refers to the cost of labor L and r to the cost of capital K , by choosing the right mix of factor inputs. Taking the ratio of the first-order conditions, $F_L - \lambda w = 0$ and $F_K - \lambda r = 0$, we obtained the profit-maximizing condition in which the marginal rate of technical substitution, F_L/F_K , equals the relative price of labor or the factor-price ratio, w/r . In short, the employment decisions of firms depend on how they respond to changes in the relative prices of factor inputs.

Within firms, using the above framework, there will be three interrelated scenarios in which it is possible to determine how automation disrupts the labor market. These scenarios depend on different forces and factors that could shape the automation decisions of firms.

Scenario 1. Automation leads to job displacement.

This will be the case when the elasticity of substitution, $\sigma = \frac{d\ln(K/L)}{d\ln(w/r)}$, derived from the above framework, holding the output constant, approaches infinity, which implies that the factor inputs are perfect substitutes. This scenario will depend on how easily firms can automate activities that human labor previously performed. First, firms are most likely to consider the amount of fixed capital costs. Automation displaces human labor if the marginal cost associated with it tends to be less than a worker's wages. Over time, one would expect the marginal cost of automation to be lower than the wages, which may lead firms to decide to substitute human labor with the automated system. Second, firms might consider the social acceptance of technology. This scenario also depends on the work dimension, that is, whether tasks are routine and whether they require cognitive skills. Jobs that machines are more likely to replace involve mainly routine and manual tasks.

Scenario 2. Automation increases productivity, thereby increasing the demand for other tasks for human labor.

The labor substitution mechanism in the first scenario would certainly be one of the major forces that would cause labor disruptions within firms. Considering the first scenario, Scenario 2 asserts that the potential increase in productivity owing to automation adoption will lead to a higher demand for labor. Productivity improvement lowers production costs, which will lead to lower prices of goods and services. As the law of demand and supply suggests, it will result in a higher demand for goods produced and services delivered, which will subsequently encourage firms to hire more laborers, especially to handle the non-automated tasks involved in the production.

Scenario 3. Automation produces new tasks for human labor.

Closely related to the second scenario, Scenario 3 exemplifies the case in which automation creates new tasks that require human labor. Acemoglu and Restrepo (2018) called it the reinstatement effect, which could arise when, following the automation of some or most of the production process, there are new functions and activities that only humans can perform or that humans can perform better than machines. For example, maintenance functions or other technical skills like programming will be necessary to ensure that machines function well.

4. EMPIRICAL ANALYSIS

We used the World Bank Enterprise Survey dataset for the Philippines for the year 2015 in conducting the empirical exercises. The survey used the stratified random sampling method, which resulted in a sample of 1,335 firms across different industries, establishment sizes, and locations (Table 1).

Table 1: Respondent Firms by Firm Size, Industry, and Region

Firm Size and Industry	Region				Total
	<i>Metro Manila</i>	<i>Central Luzon</i>	<i>Calabarzon</i>	<i>Metro Cebu</i>	
<i>Small (5–19 employees)</i>					
Manufacturing	128	67	80	58	333
Retail trade	37	14	18	10	79
Other services	30	10	12	10	62
<i>Medium (20–99 employees)</i>					
Manufacturing	147	82	108	48	385
Retail trade	22	6	9	1	38
Other services	26	7	11	8	52
<i>Large (100 and more employees)</i>					
Manufacturing	93	49	107	54	303
Retail trade	18	10	11	7	46
Other services	17	8	5	7	37
Total	518	253	361	203	1,335

Source: World Bank (2015).

4.1 Firms' Hiring Decisions

We derived the dependent variable, the hiring choices of firms, using the employment information that the survey questionnaire sought. The respondents reported the number of permanent and full-time employees during the last fiscal year (FTE_0) and three fiscal years ago (FTE_{-3}). Given the information on employment for the two different periods, firms' hiring decision y_{ni} can take the following categorical values:

$$y_{ni} = \begin{cases} 1 & \text{if } FTE_0 < FTE_{-3} \\ 2 & \text{if } FTE_0 = FTE_{-3} \\ 3 & \text{if } FTE_0 > FTE_{-3} \end{cases}$$

To observe the depth of labor market disruptions, we calculated the compounded annual growth of the permanent and full-time employment during the three-year period (FTE_{CAGR}) and broke down categories 1 and 3, classifying the double-digit compounded annual growth rate (both positive and negative) as indicating high labor market disruption, with single-digit growth indicating low expansion or reduction. Hence, we derived the following hiring decision choices:

$$y_{ni} = \begin{cases} 1 & \text{if } FTE_{CAGR} \leq -10\% \\ 2 & \text{if } -10\% < FTE_{CAGR} < 0 \\ 3 & \text{if } FTE_{CAGR} = 0 \\ 4 & \text{if } 0 < FTE_{CAGR} < 10\% \\ 5 & \text{if } FTE_{CAGR} \geq 10\% \end{cases}$$

4.2 Firms' Decision and Propensity to Automate

We denoted the automation decision with a dummy variable that takes the value of one if a firm had automated its manual processes either fully or partially to introduce a new and improved product or service and zero otherwise. To check the robustness of the results, we derived an index measuring firms' propensity to automate with the following components: (i) the adoption of new technology, (ii) the undertaking of research and development activities, (iii) the use of foreign-licensed technology, (iv) the existence of a company website, and (v) purchases or licensing of any patented or non-patented inventions or other types of knowledge to develop new products and services. For simplicity, the index imposes equal weights on each component and overall, taking values ranging between zero (less likely to automate) and one (more likely to automate).

4.3 Estimation Strategy

Guided by the conceptual framework, we derived an empirically tractable specification that attempts to model the hiring decisions of firms operating in the Philippines and determine how their automation decisions shape them. Firms are likely to choose an alternative that maximizes their profit. While we cannot easily predict a firm's choice, we can derive the probability that firm n will choose i among the alternatives by maximizing the log-likelihood function over parameters β of observed explanatory variables x :

$$\ln L(\beta) = \sum_{i=1}^N \sum_{j=1}^J y_{nj} \ln \frac{e^{x'_n \beta_i}}{\sum_j e^{x'_n \beta_j}} \quad (1)$$

where y_{nj} denotes the hiring choice of firm n with j as the base category over the five choices. Since we are interested in understanding how firms' automation decision influences their hiring decision, among the explanatory variables, we focus on the variable denoting automation, specifically x_k .

4.3.1 Control Variables

The explanatory variables controlling for firm-specific characteristics and sector and location effects include labor productivity (measured as sales divided by the total number of employees and expressed in logs), the age of the firm (which enters in a quadratic form), the size of the firm (small, medium, and large), the sectoral classification (manufacturing, retail trade services, and other services), and the regional location (Metro Manila, Central Luzon, Calabarzon, and Metro Cebu).

4.3.2 Robustness Check

To check whether the results are robust, we conducted similar multinomial logistic regressions but used the calculated index of automation propensity in lieu of the automation dummy from the baseline model. This alternative indicator is also an attempt to address the potential time mismatch involved in the automation dummy variable and firms' hiring choices. The mismatch arises from not knowing exactly when firms adopted automation during the past three fiscal years, which could distort the association between automation and hiring decisions. The index of automation propensity, on the other hand, acts like an additional observed firm-specific characteristic that may influence the depth of employment changes within firms.

4.4 Analyzing the Disproportionate Effect on Female and Low-Skilled Workers

To contribute to the ongoing policy debate on the future of work amid automation, we assessed how firms' propensity to automate disrupts the labor market structure. Is there potential bias against women workers, or will automation perpetuate social inequality by favoring skilled workers over unskilled ones? To answer these questions, we estimated ordinary least squares regressions of the following specification:

$$y_i = \alpha + \beta automation_i + \mathbf{x}'\gamma + \varepsilon_i, \quad (2)$$

where $automation_i$ refers to firm i 's derived index of automation propensity and \mathbf{x}' is a vector of control variables that include labor productivity, the age of the firm, the size of the firm, the sector to which the firm belongs, and the firm's location. ε_i denotes the stochastic error term.

The dependent variable y_i represents the derived ratios to total full-time employment of the following: (i) female employment, (ii) non-production employment, (iii) female non-production employment, (iv) unskilled employment, (v) female unskilled employment, and (vi) female temporary or seasonal employment. Here, we tried to determine whether automation tends to be skill biased, which favors skilled over unskilled workers. We also attempted to check whether automation tends to favor male over female workers, particularly for unskilled, non-production, and temporary and seasonal workers.

Table 2 displays the descriptive statistics of the variables that the study used. The firms under study are heterogeneous in terms of age, with a mean of 22 years but a standard deviation of 15 years. The labor productivity (*in logs*) across firms exhibits little dispersion, while the opposite is apparent for automation adoption and the index of automation propensity. As we expected, given the three-year period of the survey that the study used, the hiring decision variable nears the value of three, which suggests no employment reduction or expansion, as we defined above.

Table 2: Summary Statistics of the Variables in the Study

Variables	Obs.	Mean	Std Dev.	Min.	Max.
Firm's age (<i>difference between 2015 and the year of establishment</i>)	1,311	21.998	15.551	1	161
Labor productivity (<i>expressed in logs</i>)	1,209	14.004	1.782	7.706	21.115
Automation adoption (<i>takes the value 1 if yes; otherwise 0</i>)	1,319	0.366	0.482	0	1
Index of automation propensity					
<i>i. Adoption of foreign-licensed technology</i>	1,335			0	1
<i>ii. Use of new technologies</i>	1,335			0	1
<i>iii. Undertaking of research and development activities</i>	1,335			0	1
<i>iv. Existence of a company website</i>	1,335			0	1
<i>v. Purchases or licensing of inventions, patented or not</i>	1,335			0	1
Overall index	1,335	0.240	0.229	0	1
Hiring decision	1,219	3.185	0.957	1	5
Derived ratios					
<i>Female to total full-time employment</i>	1,325	0.087	0.198	0	1
<i>Non-production to total full-time employment</i>	1,004	0.325	0.203	0	1
<i>Female non-production to total full-time employment</i>	1,004	0.000	0.004	0	0.082
<i>Unskilled to total full-time employment</i>	998	0.118	0.204	0	0.883
<i>Female unskilled to total full-time employment</i>	998	0.040	0.106	0	0.706
<i>Female temporary to full-time employment</i>	1,300	0.189	0.323	0	1

Source: Authors' calculation from World Bank (2015).

5. EMPIRICAL FINDINGS

The initial assessment of the Philippine labor market structure in Section 2 revealed the potential vulnerability of the country in the event of wide-scale automation adoption. Given the current low uptake of new technologies among Philippine enterprises, we expected few or no significant labor market disruptions to take place in the near term. However, for policy purposes, it is essential to understand as early as possible how firms' decisions or intention to adopt either partially or fully automated processes shape their hiring decisions.

Table 3 presents the number of firms that did and did not adopt partially or fully automated processes to develop new products or services during the last three fiscal years. One can easily observe that, consistent with the ILO survey results, relatively few (i.e., only 37% of the respondent firms) adopted automation to the partial or full extent. The table also presents their corresponding hiring decisions. It is worth noting that firms that undertook partial or full automation are likely either to retain or to increase their overall number of permanent and full-time employees rather than reducing their labor force. We conducted a chi-squared test, and the results validated the statistical significance of the association between the two decisions that firms face: $\chi^2(4, N = 1319) = 18.32, p < .001$. Thus, a relationship exists between automation decisions and hiring practices; in general, firms that adopt automation technologies are more likely to hire workers.

Table 3: Hiring and Automation Decisions

Hiring/Automation Decisions	No Automated Process Adopted	Adopted Partial or Full Automation	Total
<i>Decision 1: Fire</i>	120 (62%)	73 (38%)	193 (100%)
High: $FTE_{CAGR} \leq -10\%$	47 (71%)	19 (29%)	66 (100%)
Low: $-10\% < FTE_{CAGR} < 0$	73 (57%)	54 (43%)	127 (100%)
<i>Decision 2: Maintain the status quo</i>	454 (68%)	216 (32%)	670 (100%)
<i>Decision 3: Hire</i>	185 (54%)	157 (46%)	342 (100%)
Low: $0 < FTE_{CAGR} < 10\%$	116 (57%)	89 (43%)	205 (100%)
High: $FTE_{CAGR} \geq 10\%$	69 (50%)	68 (50%)	137 (100%)
Total	759 (63%)	446 (37%)	1,205 (100%)

Note: Row percentages in parentheses.

Source: Authors' calculation from World Bank (2015).

We conducted several statistical analyses to assess the baseline model and the corresponding results. We conducted likelihood ratio tests to check the validity of the independent variables for inclusion in the baseline model. We found that our choice of variables to model firms' hiring decision was statistically significant. We also performed likelihood ratio tests for combining alternatives to determine whether firms' hiring choices are indistinguishable with respect to the variables in the baseline model. The test showed that we should combine no categories; thus, there are significant differences between categories. Lastly, our model did not violate the independence of irrelevant alternatives tests.

Finding 1. Firms that are more likely to automate tend to hire more, *ceteris paribus*.

The results suggest that firms that have adopted partial or full automation to develop their new products or services on average hire more workers than their counterpart firms. Table 4 shows the result of the baseline multinomial logistic regression that models firms' hiring choices using only three categories, specifically fire, maintain, and hire. The coefficient estimate indicates that, if a firm decides to automate partially or in full the processes in its operation that were once conducted manually, the multinomial log-odds for hiring more employees relative to firing or laying off is likely to increase by 0.3 units after controlling for other relevant observed time-invariant characteristics. While statistically non-significant, the coefficient estimate for the status quo choice seems suggestive of the potential labor market disruption, even in the short run, it being the least popular choice among firms adopting automation.

The above results show the general pattern that we expected to occur during automation. We can glean the degree or magnitude of such a pattern from Table 5. Based on the coefficient estimates, with reference to the choice of more than 10% of worker layoffs, firms that adopted full or partial automation lean more toward choosing to hire more employees. It is worth noting that the extent of hiring more than 10% even exhibits the highest likelihood of being firms' choice. Automation adoption will indeed cause labor market disruption in the Philippines, as the results also suggest that maintaining a status quo, whereby no change in employment will occur, is the least popular option among firms. This is also generally observable from the results of the alternative model (see Appendix Table 1), which is robust to firms choosing to hire more than 10%. The results reveal that the relative probability of hiring rather than laying off in firms with a greater propensity to automate far outweighs the relative probability of firms that are less likely to automate, keeping other factors constant.

Table 4: Result of the Multinomial Logistic Regression of the Firms' Hiring Model
(Three Categories)

Variables	Maintain Status	
	Quo	Hire
	<i>Reference = Fire</i>	
Automation decision (<i>takes the value 1 if yes and 0 otherwise</i>)	-0.227 (0.180)	0.334* (0.194)
Labor productivity (<i>expressed in logs</i>)	0.082 (0.052)	0.101* (0.058)
Firm age	0.018 (0.013)	-0.005 (0.013)
Firm age squared	0.000 (0.000)	0.000 (0.000)
Firm size (<i>baseline = small</i>)		
Medium-sized enterprises	-0.419** (0.209)	-0.196 (0.230)
Large enterprises	-0.218 (0.232)	0.033 (0.255)
Industry (<i>baseline = manufacturing</i>)		
Retail services	0.608** (0.302)	-0.028 (0.345)
Other services	0.247 (0.308)	0.553* (0.320)
Region (<i>baseline = Metro Manila</i>)		
Metro Cebu	0.055 (0.265)	-0.085 (0.286)
Central Luzon	0.13 (0.247)	-0.208 (0.271)
Calabarzon	0.068 (0.218)	-0.439* (0.242)
Constant	-0.038 (0.744)	-0.681 (0.819)
Log likelihood	-1,054.527	
LR chi-square	51.361	
Number of observations	1090	

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

Table 5: Result of the Multinomial Logistic Regression of the Firms' Hiring Model (Five Categories)

Variables	Fire	Maintain Status Quo	Hire	
	Low	No Change	Low	High
	<i>Reference = FTE_{CAGR} ≤ -10%</i>			
Automation decision (<i>takes the value of 1 if yes and 0 otherwise</i>)	0.700** (0.344)	0.253 (0.299)	0.634** (0.324)	1.067*** (0.34)
Labor productivity (<i>expressed in logs</i>)	-0.135 (0.096)	-0.005 (0.081)	0.042 (0.089)	-0.026 (0.094)
Firm age	-0.079* (0.042)	-0.054 (0.04)	-0.067 (0.042)	-0.087** (0.042)
Firm age squared	0.001** (0.001)	0.001 (0.001)	0.001 (0.001)	0.001** (0.001)
Firm size (<i>baseline = small</i>)				
Medium-sized enterprises	0.482 (0.381)	-0.103 (0.318)	0.411 (0.358)	-0.249 (0.373)
Large enterprises	0.453 (0.429)	0.076 (0.358)	0.658* (0.397)	-0.106 (0.417)
Industry (<i>baseline = manufacturing</i>)				
Retail services	-0.139 (0.568)	0.516 (0.458)	-0.474 (0.540)	0.264 (0.525)
Other services	0.324 (0.614)	0.462 (0.541)	0.666 (0.569)	0.924 (0.581)
Region (<i>baseline = Metro Manila</i>)				
Metro Cebu	0.242 (0.520)	0.231 (0.460)	-0.159 (0.501)	0.391 (0.508)
Central Luzon	-0.770* (0.446)	-0.328 (0.359)	-0.755* (0.403)	-0.553 (0.425)
Calabarzon	-0.198 (0.403)	-0.065 (0.345)	-0.546 (0.379)	-0.64 (0.414)
Constant	2.900** (1.416)	2.712** (1.206)	0.992 (1.327)	1.828 (1.393)
Log likelihood	-1,365.4			
LR chi-square	92.897			
Number of observations	1,090			

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

To demonstrate clearly the disruptive effect of automation in the domestic labor market, Table 6 displays the coefficient estimates with the corresponding relative odds, comparing all possible combinations of choices. Highlighted are the statistically significant estimates, which suggest that the automation adoption of firms operating in the Philippines is associated with job creation. The relative probability of hiring is double that of firing among firms that decided to automate relative to firms that did not, given that other factors remain constant. It is also the case relative to maintaining the status quo, suggesting disruptive consequences arising from the automation decision. Note that firing, albeit low, at less than 10%, has a higher relative probability than maintaining the status quo among firms that adopted automation.

Table 6: Relative Odds of Firms' Hiring Choices

Hiring Choices of Firms	Coefficient	z	P>z	Relative Odds
Hire versus fire				
5 versus 1	1.067	3.141	0.002	2.908
5 versus 2	0.367	1.394	0.163	1.444
4 versus 1		1.960	0.050	1.886
4 versus 2	-0.066	-0.271	0.787	0.936
Hire versus maintain the status quo				
5 versus 3	0.814	4.007	0.000	2.258
4 versus 3	0.382	2.157	0.031	1.464
Maintain the status quo versus fire				
3 versus 1	0.253	0.845	0.398	1.288
3 versus 2	-0.447	-2.124	0.034	0.639

Note: We computed the relative odds by exponentiating the estimated coefficients.

Source: Authors' estimates.

We also computed the difference in the probability of firms' hiring choices with respect to their automation adoption. Table 7 shows that the probability of hiring more is on average about 7 percentage points higher for firms that have adopted automation than for those that have not. As expected, firms that have automated processes that were previously completed manually exhibit around a 10 percentage point lower probability of maintaining the status quo. There are also chances of firing (only at the moderate scale) during automation, but these results are not statistically significant.

Table 7: Average Marginal Effects ($\partial y/\partial x$) of Automation on Hiring Choices

Hiring Choices of Firms	($\partial y/\partial x$)	Std Err.	z	P>z
<i>Decision 1: Fire</i>				
High: $FTE_{CAGR} \leq -10\%$	-0.025	0.016	-1.58	0.114
Low: $-10\% < FTE_{CAGR} < 0$	0.026	0.019	1.37	0.169
<i>Decision 2: Maintain the status quo</i>	-0.102	0.031	-3.32	0.001
<i>Decision 3: Hire</i>				
Low: $0 < FTE_{CAGR} < 10\%$	0.030	0.023	1.31	0.189
High: $FTE_{CAGR} \geq 10\%$	0.070	0.020	3.56	0.000

Source: Authors' estimates.

Finding 2. The likelihood of net job creation associated with the automation decision differs across industries.

We conducted additional empirical exercises in an attempt to identify the potential heterogeneity of the above finding. In doing so, we found significantly varying responses from the sample firms in the "other services" sector, while those of the firms in retail services exhibit ambiguous responses, given that their coefficient is not statistically significant. Table 8 shows that only the manufacturing firms display a greater likelihood of net job creation on adopting partial or full automation in their operation. It could be the case that the relatively high labor productivity in the manufacturing industry allows firms to create additional jobs as the output per worker increases. On the other hand, firms falling into the other services industry, which include those in the hotel and restaurant

business, logistics, and IT consulting and development, among other related services, have a higher likelihood of net job losses as they adopt partial or full automation.

Table 8: Sectoral Heterogeneity of Hiring Decisions

Variables	Fire	Maintain Status Quo	Hire	
	Low	No Change	Low	High
	<i>Reference = FTE_{CAGR} ≤ -10%</i>			
Automation decision (<i>takes the value of 1 if yes and 0 otherwise</i>)	0.897** (0.387)	0.463 (0.341)	0.848** (0.366)	1.294*** (0.390)
Automation and industry interaction term				
<i>Retail services</i>	-0.451 (1.165)	-0.199 (0.957)	-0.37 (1.107)	-0.622 (1.076)
<i>Other services</i>	-2.145 (1.365)	-2.583** (1.242)	-2.390* (1.283)	-2.223* (1.302)
Industry (<i>baseline = manufacturing</i>)				
<i>Retail services</i>	0.016 (0.713)	0.557 (0.555)	-0.354 (0.684)	0.525 (0.663)
<i>Other services</i>	1.378 (1.103)	1.67 (1.028)	1.825* (1.055)	2.000* (1.079)
Labor productivity (<i>expressed in logs</i>)	-0.135 (0.097)	-0.005 (0.081)	0.042 (0.089)	-0.026 (0.094)
Firm age	-0.081* (0.042)	-0.057 (0.040)	-0.070* (0.042)	-0.089** (0.042)
Firm age squared	0.001** (0.001)	0.001 (0.001)	0.001 (0.001)	0.001** (0.001)
Firm size (<i>baseline = small</i>)				
<i>Medium-sized enterprises</i>	0.476 (0.381)	-0.113 (0.319)	0.404 (0.358)	-0.25 (0.374)
<i>Large enterprises</i>	0.464 (0.429)	0.087 (0.358)	0.670* (0.398)	-0.092 (0.417)
Region (<i>baseline = Metro Manila</i>)				
<i>Metro Cebu</i>	0.248 (0.521)	0.233 (0.461)	-0.155 (0.502)	0.401 (0.509)
<i>Central Luzon</i>	-0.769* (0.446)	-0.328 (0.360)	-0.755* (0.403)	-0.55 (0.426)
<i>Calabarzon</i>	-0.217 (0.405)	-0.088 (0.347)	-0.568 (0.381)	-0.659 (0.416)
Constant	2.876** (1.414)	2.698** (1.204)	0.971 (1.326)	1.79 (1.390)
Log likelihood	-1,362.37			
LR chi-square	98.956			
Number of observations	1,090			

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

Finding 3. Labor market disruptions that deserve policy actions are apparent.

Table 9 summarizes the results after estimating Equation 2. The empirical exercises reveal that, keeping other factors constant, the expectation is that the job prospects for non-production workers will remain positive in firms that are more likely to introduce new production technologies, including those that could automate some tasks. This finding is intuitive, as non-production workers are highly involved in managerial and administrative activities as well as sales, fulfilling tasks that are not easily automatable. While there are already online platforms in the Philippines to conduct selling activities, sales workers remain relevant for activities that require human contact. Consistent with the recent findings of Krieger-Boden and Sorgner (2018), we also found an indicative good prospect for female full-time workers in firms that are more likely to adopt automation. Largely thanks to the historical expansion in educational attainment, the female workforce in the Philippines has the potential to handle tasks that may require higher skills during automation and other technological adoptions at firms across the state.

Table 9: Propensity to Automate and Employment Structure

Ratio to Total Full-Time Employment	Coefficient Estimates
(Equation 2.1) Non-production workers	0.121*** (0.029)
(Equation 2.2) Female non-production workers	0.000 (0.001)
(Equation 2.3) Unskilled workers	0.080*** (0.030)
(Equation 2.4) Female unskilled workers	-0.000 (0.015)
(Equation 2.5) Female full-time workers	0.044*** (0.015)
(Equation 2.6) Temporary or seasonal workers	0.287 (0.186)
(Equation 2.7) Female temporary or seasonal workers	0.089* (0.043)

Note: Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

The results also suggest some potential downside risks to the labor market structure. Table 9 shows that, on average, firms with a higher propensity to automate have a larger share of low-skilled workers than the total full-time employment. While this may seem positive, the result also indicates the lower flexibility among lower-skilled workers to move to other jobs, especially in the instance of full deployment of automated processes. Bessen et al. (2019) reached similar conclusions following their analysis of the impact of automation on Dutch workers. They found that automation is less likely to displace lower-skilled workers, defined as those in the lower wage ranks, than higher-skilled workers. However, they also pointed out that, if these lower-skilled workers leave work during automation, they will find it very difficult to source new employment prospects. What is interesting to note is that, after evaluating the survey data, we found that firms that had adopted automated processes are more likely to offer formal training programs, which may provide opportunities for their low-skilled employees to gain and upgrade skills. Another potential downside from automation based on the results is the associated rise

in temporary and seasonal workers in firms that are more likely to automate. These types of workers often lack favorable labor market conditions, including the necessary support mechanisms and bargaining power. The number of female workers in this work category is also likely to rise. The societal expectations of the role of women, especially mothers, in households may explain this trend. Meanwhile, it is hard to tell whether the rise of the gig economy, which often involves short-term contracts or freelance work, could explain the expectations of an increased demand for temporary or seasonal workers. The gig economy in the Philippines, as well as jobs with flexible work arrangements, like in many other countries, continues to rise amid the advances in technology and related infrastructure.

6. CONCLUSION AND POLICY IMPLICATIONS

Our study presented a novel way to estimate the potential labor impact of automation, that is, through the lens of firms. The empirical exercises analyzing firms' hiring choices reported that the Philippine labor market outlook remains promising in the age of automation. The study generally found that the automation revolution can benefit the labor force, at least in the short run. The productivity effect seems to be at work, offsetting the possible job losses resulting from automating tasks. Our results reveal that firms that have adopted automation tend to hire more rather than fewer employees. Indeed, there is an expectation that firms' adoption of new and advanced technologies will introduce disruptions into the labor market. Maintaining the status quo is the least likely outcome among firms that are considering automating processes.

The automation revolution is also changing the landscape of the country's labor market. Non-production workers have good job prospects that could be due to them occupying roles that are not easily automatable. Further, these workers tend to have higher skills, making them more flexible and able to carry out other non-automated tasks. Interestingly, we did not find evidence that female workers will be at a disadvantage once automation takes place at a wider scope and scale. One concern, however, is the possible trend or tendency toward temporary and seasonal workers, which may make workers vulnerable to economic shocks. Why this trend is likely to occur deserves further analysis.

The long-run labor market consequences of further automation remain uncertain. The short-run overall gains in employment in our findings may not take place in the future when automation and other more advanced technologies, such as artificial intelligence, further revolutionize the world of work. The results only reflect short-run labor market disruptions and cannot explain the longer-term consequences of automation. In addition, as an earlier section discussed, the potential time mismatch involved in the automation indicator and firms' hiring choices does not allow for an interpretation of the results as an immediate reaction of firms that have automated some or all functions in producing products or delivering services. Nevertheless, the results give an indication of the net direction of employment changes.

In the short run, the impact of automation is most likely to vary at the individual level and thus requires policy intervention. There are workers who are potentially at risk of job displacement during the process of automation. While income risk will be the most direct implication of job displacement, there are also adverse consequences for one's psychological well-being. Displaced workers are often more at risk of depression, anxiety, and stress. If support services are available for affected workers, then the process could be smooth and painless; otherwise, it could have adverse effects on individuals' mental health and economic prospects. In this case, the government should

put in place support services in the form of assistance in the short run and human capital development in the long run.

An important policy lever in the automation revolution is education and training. The adoption of new and advanced technologies and processes is inevitable in profit-maximizing firms. During this process, new tasks may emerge and most likely will require new skill sets. Workers should possess the right set of skills and competencies, making them more flexible and therefore more able to occupy new roles. Automation, studies have revealed, tends to favor cognitive skills, such as social and communication skills. Thus, the government needs to ensure that the current curriculum is in line with the set of competencies that firms will demand in the future. Otherwise, the anxiety over a loss of work in the future would become a reality.

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Dataset

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APPENDIX

Appendix Table 1: Robustness Check: Multinomial Logistic Regression of the Firm Hiring Model Using the Index of Automation Propensity

Variables	Fire	Maintain Status Quo	Hire	
	Low	No Change	Low	High
	<i>Reference = FTE_{CAGR} ≤ -10%</i>			
Index of automation propensity (<i>1 being the highest and 0 the lowest</i>)	0.063 (0.741)	-0.37 (0.637)	0.553 (0.686)	2.100*** (0.716)
Labor productivity (<i>expressed in logs</i>)	-0.105 (0.097)	0.019 (0.082)	0.059 (0.090)	-0.043 (0.096)
Firm age	-0.072* (0.042)	-0.049 (0.040)	-0.061 (0.042)	-0.078* (0.041)
Firm age squared	0.001* (0.001)	0.001 (0.001)	0.001 (0.001)	0.001* (0.001)
Firm size (<i>baseline = small</i>)				
Medium-sized enterprises	0.434 (0.380)	-0.115 (0.319)	0.368 (0.358)	-0.406 (0.374)
Large enterprises	0.453 (0.438)	0.115 (0.367)	0.631 (0.406)	-0.334 (0.427)
Industry (<i>baseline = manufacturing</i>)				
Retail services	-0.139 (0.567)	0.512 (0.457)	-0.467 (0.539)	0.322 (0.525)
Other services	0.288 (0.613)	0.429 (0.541)	0.65 (0.568)	0.998* (0.579)
Region (<i>baseline = Metro Manila</i>)				
Metro Cebu	0.157 (0.518)	0.235 (0.459)	-0.192 (0.500)	0.354 (0.507)
Central Luzon	-0.813* (0.445)	-0.366 (0.359)	-0.756* (0.403)	-0.466 (0.423)
Calabarzon	-0.247 (0.403)	-0.091 (0.346)	-0.528 (0.380)	-0.594 (0.415)
Constant	2.699* (1.412)	2.495** (1.209)	0.787 (1.328)	1.853 (1.395)
Log likelihood	-1,372.3			
LR chi-square	106.5			
Number of observations	1,103			

¹ Using the estimated propensity to automate index as an alternative indicator for automation.

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.