Automation in Indonesia:
Productivity, Quality, and Employment

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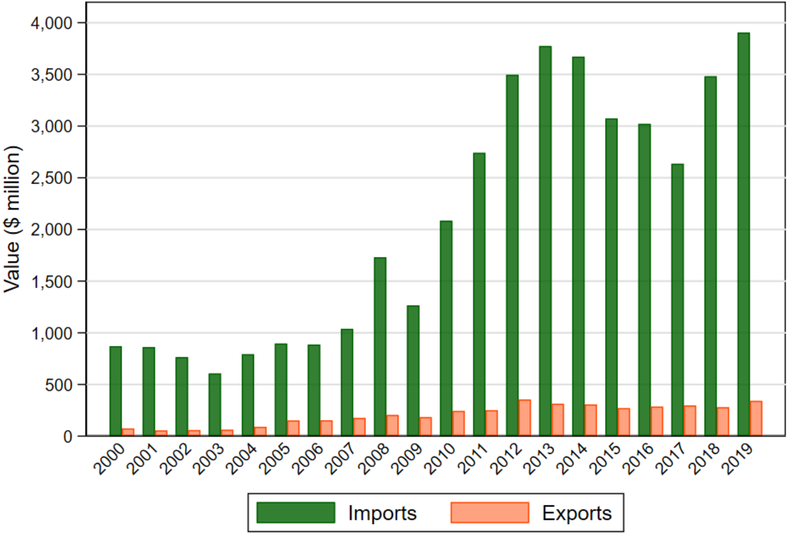
Motivation

- Since the 1980s, A notable increase in wages in developed countries has caused increasing usages of automation equipment
  - Automation equipment helps human workers perform their tasks more efficiently
  - It also improves precision, accuracy, and reliability, thereby reducing overall costs while also raising product quality and overall firm productivity
  - It may also displace workers
- While a number of studies have examined the effects of automation in developed countries, related studies about developing countries are still rare
- In this chapter, we examine 'automation in Indonesia' for two reasons:
  1. Indonesia has one of the highest growth rates in automation among developing countries (average annual growth of 24% for more than a decade since 2007)
  2. Almost 60% of Indonesia's population is in the labor force. So the replacement of workers by automation equipment can be expected to create huge social challenges.

Exports and Imports of Automation Equipment by Indonesia



Source: Authors' calculation from United Nations Comtrade data.

In This Chapter

- We measure Indonesia's firm-level usage of automation equipment based on merged micro-level data sets
  - Focus on the direct imports of automation equipment by Indonesian manufacturers
  - A broader measure for automation equipment: not limited to industrial robots
- We examine the relationships between firm-level automation status and various firm outcomes. In the cross-sectional comparisions, we find that automators
  - produce more outputs, hire more workers, and have relatively higher productivity
  - pay higher wages, have lower labor shares, and use capital more intensively
  - produce more varieties of outputs and are more actively engaged in exports and imports, and produce outputs of relatively higher inferred quality
- Using a long-difference specification, we also find that automators:
  - see larger increases in outputs and productivity, experience larger increases in export shares and higher inferred product quality, and employ more production workers
- We propose a theoretical framework that incorporates firm-level automation decisions to rationalize our empirical results

Data: Identifying Automation at the Firm Level, 2008–2012

- Annual survey of large and medium-sized manufacturing firms in Indonesia:
  - $\approx 35,000$ firms annually
  - records gross output, value added, number of production and non-production workers, wages, capital, materials usage, and export and import shares, etc.
  - information on outputs and raw material purchases at the firm-product level
- Firm-level customs information:
  - value, quantity, HS product code, and import country of origin, as well as export destination countries for each Indonesian firm in a given year
  - essential for identifying direct imports of automation equipment at the firm level
- We identify automation following Humlum (2019) and Acemoglu et al. (2020):
  - collect the HS 6-digit codes used by Acemoglu and Restrepo (2021) to define industrial automation equipment for each firm in the customs data.
  - including industrial robots, numerically controlled machines, automatic machine tools, weaving and knitting machines, regulating and control instruments, etc.
  - Caveat: only direct imports of automation equipment during 2008–2012; not purchases of equipment from domestic wholesalers/retailers or purchases prior to 2008

Direct Imports of Automation Equipment by Manufacturing Firms

	Growth (in %)				
Equipment Type	**2008**	**2009**	**2010**	**2011**	**2012**
Automatic machine tools	.	-67.59	286.45	21.24	24.73
Automatic welding machines	.	-64.11	29.85	148.51	21.47
Industrial robots	.	-87.71	1953.86	-11.21	88.86
Numerically controlled machines	.	-45.70	245.17	59.78	61.80
Other textile dedicated machinery	.	-14.86	50.98	83.88	20.98
Regulating & control instruments	.	49.13	-6.71	23.38	29.23
Weaving & knitting machines	.	-64.39	110.74	52.15	-41.18
Total	**.**	**-57.30**	**154.64**	**48.91**	**12.29**
	Shares (in %)				
Equipment Type	**2008**	**2009**	**2010**	**2011**	**2012**
Automatic machine tools	8.79	6.67	10.12	8.24	9.16
Automatic welding machines	4.68	3.94	2.01	3.35	3.62
Industrial robots	4.83	1.39	11.21	6.68	11.24
Numerically controlled machines	14.61	18.58	25.18	27.02	38.93
Other textile dedicated machinery	9.34	18.62	11.04	13.63	14.69
Regulating & control instruments	1.00	3.48	1.28	1.06	1.22
Weaving & knitting machines	56.75	47.32	39.16	40.02	20.96
Total	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

Source: Authors' calculation from BPS data.

Industry composition

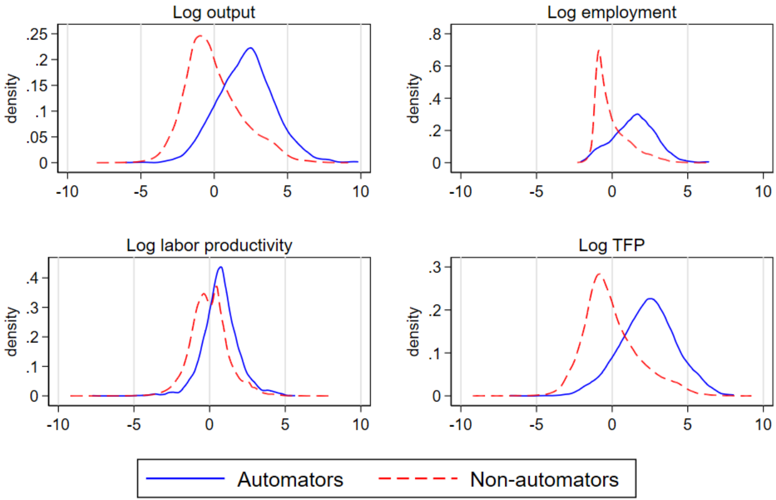
Empirical Strategy: Cross–Sectional Comparison

- We do not attempt to infer causality between automation and firm-level outcomes, but the correlations between them.
- How do automators differ from non–automators in a given industry?

$$y_{ft} = \beta^a \times a_{ft} + X_{ft} + \delta_{it} + \delta_{rt} + \epsilon_{ft} \quad (1)$$

  - y: outcome variable
  - f, t, i and r represent firm, year, International Standard Industrial Classification (ISIC) 2-digit industry code, and region (Java or not)
  - $a_{ft} = 1$ if f imported automation equipment at least once during 2008–2012
  - X_{ft}: control variables (e.g., firm export share, import share, and foreign ownership)
  - δ_{it}: industry–year fixed effects; δ_{rt} region–year fixed effects
- Focus: β^a, the 'automation premium' identified within an ISIC 2-digit industry in a given year across firms

Size and Productivity: Automators versus Non–automators



ISIC = International Standard Industrial Classification. TFP = total factor productivity.
Note: ISIC 2-digit-year fixed effects are removed.
Source: Authors' calculation from BPS data.

Automation, Size, and Productivity: Cross–Sectional Comparison

Dependent variable: (in log)	(1) Output	(2) Employment	(3) Value added per worker	(4) TFP
Automation	1.389***	0.995***	0.396***	1.445***
	(0.085)	(0.060)	(0.048)	(0.112)
Export share	0.860***	0.756***	0.031	1.144***
	(0.038)	(0.026)	(0.021)	(0.045)
Import share	1.424***	0.804***	0.641***	1.316***
	(0.055)	(0.036)	(0.031)	(0.071)
Foreign-owned	1.448***	0.745***	0.708***	1.425***
	(0.046)	(0.031)	(0.028)	(0.059)
Fixed effects	industry-year, region-year			
No. of observations	110,735	110,735	109,039	69,655

TFP = total factor productivity.

Note: This table reports the cross-sectional comparisons of firm-level size and productivity measures between firms that import automation equipment and firms that do not. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Source: Authors' calculation from BPS data.

Automation and Product Quality: Cross–Sectional Comparison

Dependent variable (in log):	(1) Market share	(2) Price	(3) Inferred quality
Automation	1.175***	-0.002	0.441***
	(0.117)	(0.122)	(0.150)
Export share	0.637***	0.080**	0.369***
	(0.048)	(0.038)	(0.046)
Import share	1.165***	-0.193**	0.462***
	(0.081)	(0.075)	(0.102)
Foreign-owned	1.057***	-0.052	0.493***
	(0.062)	(0.056)	(0.070)
Fixed effects	HS4-year, region-year		
No. of observations	118,570	118,570	118,570

HS = Harmonized System.
Note: This table reports the cross-sectional comparisons of product-level characteristics between firms that import automation equipment and firms that do not. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

Empirical Strategy: Long-Difference Specification

- We analyze whether changes in firm-level outcomes are associated with automation status using a long-difference specification, similar to Acemoglu et al. (2020):

$$\Delta y_{f,2012-2008} = \beta^{\Delta a} \times \Delta \mathrm{a}_{f,2012-2008} + \mathrm{X}_{f,2008} + \delta_i + \delta_r + \epsilon_f \tag{2}$$

  - $\Delta y_{f,2012-2008}$: long-difference of firm f's outcome variable y during 2008–2012
  - $\Delta \mathrm{a}_{f,2012-2008} = 1$ if firm f imported any automation equipment during 2008–2012
  - $\mathrm{X}_{f,2008}$: lagged variables to control for initial conditions (e.g., log labor productivity, log employment, log capital–labor ratio, export share, import share)
  - δ_i: ISIC 2-digit industry fixed effect; δ_r: region fixed effect

- The long-difference results reflect associations between automation decisions and changes in firm-level outcomes, rather than causal effects of automation

Automation, Size, and Productivity: Long-Difference Specification

Dependent variable: (log difference)	(1) Output	(2)	(3) Value added	(4)	(5) TFP	(6)
Automation	0.145***	0.189***	0.167***	0.212***	0.223***	0.204***
	(0.056)	(0.072)	(0.056)	(0.074)	(0.074)	(0.074)
Lagged log labor productivity	-0.350***	-0.385***	-0.446***	-0.548***	-0.163***	-0.175***
	(0.011)	(0.019)	(0.012)	(0.020)	(0.012)	(0.016)
Lagged log employment	-0.046***	-0.013	-0.008	0.035**	-0.083***	-0.076***
	(0.010)	(0.014)	(0.011)	(0.014)	(0.012)	(0.013)
Lagged foreign ownership	0.157***	0.074	0.182***	0.065	0.063	0.058
	(0.041)	(0.054)	(0.041)	(0.056)	(0.053)	(0.057)
Lagged export share	-0.057	-0.116**	-0.064*	-0.098**	-0.103**	-0.115**
	(0.038)	(0.047)	(0.038)	(0.048)	(0.042)	(0.046)
Lagged import share	0.158***	0.078	0.214***	0.154**	0.114*	0.074
	(0.048)	(0.066)	(0.048)	(0.069)	(0.058)	(0.065)
Lagged log non-production share		0.045***		0.081***		0.011
		(0.011)		(0.012)		(0.011)
Lagged log K/L ratio		0.070***		0.118***		0.034***
		(0.010)		(0.010)		(0.009)
Fixed effects	industry, region					
No. of observations	17,496	8,947	17,288	8,841	9,921	7,934

Note: This table reports how firm size and productivity measures vary with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

Automation and Employment: Long-Difference Specification

Dependent variable: (log difference)	(1) Employment	(2)	(3) Production employment	(4)	(5) Non-production employment	(6)
Automation	0.113***	0.204***	0.115***	0.230***	0.028	0.054
	(0.038)	(0.044)	(0.039)	(0.046)	(0.051)	(0.065)
Lagged log labor productivity	0.053***	0.027***	0.059***	0.025***	0.023***	0.035***
	(0.005)	(0.007)	(0.006)	(0.008)	(0.008)	(0.011)
Lagged log employment	-0.177***	-0.138***	-0.173***	-0.138***	-0.158***	-0.106***
	(0.006)	(0.008)	(0.007)	(0.009)	(0.009)	(0.012)
Lagged foreign ownership	0.008	-0.011	0.010	-0.015	0.012	0.015
	(0.026)	(0.033)	(0.028)	(0.035)	(0.036)	(0.044)
Lagged export share	0.036	-0.012	0.023	-0.039	0.098***	0.064
	(0.023)	(0.028)	(0.024)	(0.029)	(0.037)	(0.043)
Lagged import share	0.072**	0.072*	0.081***	0.061	0.036	0.071
	(0.029)	(0.037)	(0.030)	(0.039)	(0.041)	(0.053)
Lagged log non-production share		0.008		0.053***		-0.143***
		(0.006)		(0.007)		(0.010)
Lagged log K/L ratio		0.020***		0.016***		0.022***
		(0.005)		(0.005)		(0.008)
Fixed effects	industry, region					
No. of observations	17,892	9,130	17,889	9,130	13,349	7,668

Note: This table reports how firm-level employment varies with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Source: Authors' calculation from BPS data.

Automation and Product-level Outcomes: Long-Difference Specification

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: (log difference)	**Market share**		**Price**		**Quality**	
Automation	0.238	0.499*	0.221	0.294	0.478**	0.604**
	(0.243)	(0.289)	(0.155)	(0.229)	(0.223)	(0.299)
Lagged log labor productivity	-0.420***	-0.484***	-0.226***	-0.204***	-0.473***	-0.510***
	(0.033)	(0.046)	(0.026)	(0.039)	(0.036)	(0.051)
Lagged log employment	-0.178***	-0.143***	0.006	0.008	-0.091**	-0.056
	(0.036)	(0.052)	(0.030)	(0.044)	(0.037)	(0.054)
Lagged foreign ownership	0.173	0.106	0.180	0.057	0.303**	0.107
	(0.129)	(0.185)	(0.113)	(0.219)	(0.137)	(0.244)
Lagged export share	-0.065	-0.168	0.217**	0.129	0.159	0.056
	(0.108)	(0.130)	(0.106)	(0.123)	(0.120)	(0.140)
Lagged import share	0.105	-0.121	0.127	0.186	0.263	0.314
	(0.193)	(0.276)	(0.124)	(0.249)	(0.188)	(0.351)
Lagged log non-production share		-0.025		0.014		0.005
		(0.033)		(0.029)		(0.037)
Lagged log K/L ratio		0.034		0.070***		0.089***
		(0.029)		(0.024)		(0.031)
Fixed effects	HS 4-digit, region					
No. of observations	5,871	2,851	5,871	2,851	5,871	2,851

Note: This table reports how product-level outcomes vary with the imports of automation equipment over time. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Source: Authors' calculation from BPS data.

Interpreting Empirical Findings: A Simple Framework

- We propose a simple model of heterogeneous firms that make firm-level automation decisions to rationalize our empirical findings
  - Using automation equipment entails a fixed cost. This equipment lowers the unit cost of production by offering alternative technologies to complete tasks
  - Firms differ in productivity, and decide the quality of goods they produce
  - Preference is CES and the market structure is monopolistic competition
  - Automation, quality, price and sales are all endogenous decisions to a firm
- Our simple framework predicts:
  - Automators have higher output and productivity than non–automators
  - Automators produce higher-quality products
  - An ambiguous correlation b/w firm-level employment and automation: a positive size effect $\uparrow$ labor demand versus a negative substitution effect $\downarrow$ labor demand

Conclusions

- We conduct an empirical analysis of automation in Indonesia, with a particular focus on how firm-level automation is associated with different firm-level outcomes
- We measure direct imports of automation equipment by Indonesian firms and describe patterns of automation by these firms
- We find that automation decision is associated with exceptional performance, both in a cross–sectional comparison and in a long-difference specification
- We propose a simple theoretical framework of heterogeneous firms to rationalize our empirical findings

Shares of Direct Imports of Automation Equipment (in %), by Industry

ISIC 2-digit industry	2008	2009	2010	2011	2012
Food	1.34	0.46	0.19	0.83	1.12
Beverage	0.00	0.00	0.00	0.03	0.00
Tobacco	0.02	0.03	0.03	0.01	0.56
Textiles	61.21	55.32	45.43	41.50	24.91
Apparel	2.45	2.76	2.02	5.10	2.77
Leather	0.10	0.67	0.16	3.72	1.23
Wood and Straw	0.01	0.00	0.06	0.04	0.03
Paper	0.00	0.34	0.01	0.01	0.39
Printing	0.09	0.00	0.00	0.00	0.00
Chemicals	1.30	2.31	0.90	0.56	0.05
Medicine	0.00	0.01	0.00	0.00	0.00
Rubber and Plastics	2.40	7.20	3.68	3.20	5.49
Non-metallic Minerals	0.62	0.04	0.47	0.22	0.43
Basic Metals	0.68	1.89	1.91	3.54	9.70
Fabricated Metal	1.47	5.01	2.26	6.67	4.15
Computer, Electronic and Optical	0.98	3.63	2.38	2.62	3.08
Electrical Equipment	2.23	4.78	4.47	1.83	0.94
Machinery	9.62	1.73	5.57	1.13	4.40
Motor Vehicles	7.82	6.89	24.55	23.57	32.14
Other Transport Equipment	4.50	5.73	2.71	4.52	6.02
Furniture	2.49	0.11	2.20	0.03	0.72
Other Manufacturing	0.68	1.10	0.99	0.82	1.78
Repair and Installation	0.00	0.00	0.00	0.04	0.09
Total	100.00	100.00	100.00	100.00	100.00

Source: Authors' calculation from BPS data.

Type composition

Reference

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