Technology Adoption and Productivity of Korean Firms

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with

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I. Introduction

Motivation

- Technology is key to boost productivity and generate more and better-quality jobs.
- Differences in technology adoption account for a large share of the income gap between and within countries (Comin and Mestieri, 2017).
- Variations in technology adoption can generate sizable productivity dispersion across firms and industriess (Gal et al., 2019; Giorcelli, 2019; Juhasz et al., 2020).

Limitation of existing measurements of technology adoption

- Yet, most measures of technology adoption currently available is only partially measuring technology (internet, computers, platforms, or AI).
- Many researchers rely on national-level surveys on specific technologies or the adoption of frontier technologies specific to some sectors.
- If firms do not adopt the specific technology, most surveys cannot capture what technology is used instead, and fail to enquire how intensively a technology is used and for what purpose.

Firm-level Adoption of Technology (FAT) survey (Cirera et al. (2020))

- We propose the FAT survey that provides detailed information on the adoption and intensive use of several technologies associated with several business functions.
- The FAT survey identifies the key business functions carried out by firms and lists the available technologies that firms can use to perform each business function.
- In Korea, it includes a nationally representative random sample of 1,551 formal firms with five or more employees in agriculture, manufacturing, and services.

Research objectives

Utilizing the FAT survey

1. Develop new measures of technology adoption
2. Investigate the main correlates of technology adoption

Using the Korea Enterprise Data (KED)

3. Estimate production function and describe recent trends of productivity.

Using the merged data of FAT and KED

4. Explore the association between technology adoption and productivity.

Related literatures

- Technology measurement: Ryan and Gross (1943), Griliches (1957), Mansfield (1963), Trajtenberg (1990).
- Technology and productivity: Comin and Hobijn (2010) and Comin and Mestieri (2018); Jorgenson et al. (2005), Oliner, Sichel and Stiroh (2007); Hubbard (2003), Barstel, Ichniowski and Shaw (2007), Hjort and Poulsen (2019).
- Parallel to literature on management practices (Bloom and Van Reenen (2007, 2019).
  - Similarities: use survey methods and connect indices to firm productivity
  - Differences: Due to methodology and interest, we explore technology within the firm

More details on the FAT survey

Coverage

- Countries completed: Bangladesh, Ceara, Malawi, Senegal, Vietnam, India, Kenya, Korea, Chana, Burkina Faso, Poland, Georgia.
- Sectors: Agriculture, Manufacturing, and Services.

Survey structure

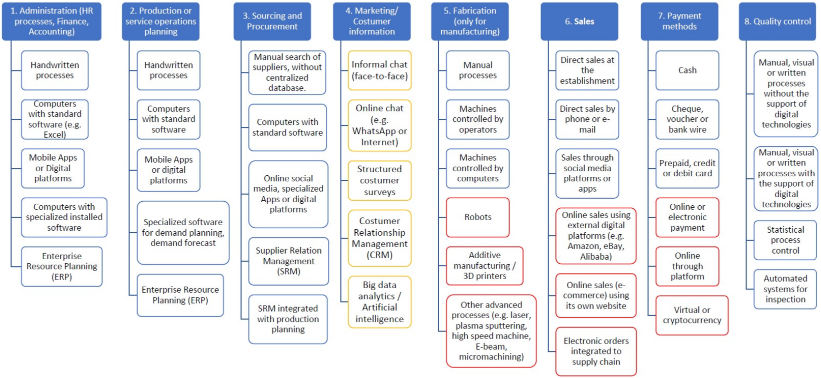
- Module A: General characteristics of the establishment
- Module B: General Business Function Technologies
- Module C: Sectoral Specific Technologies
- Module D: Drivers and Barriers for technology adoption
- Module E: Labor, Balance Sheet, and Performance

In Korea survey

- A representative random sample for agriculture, services and manufacturing from the Korea Statistical Agency.
- Sample size: 1,551 firms (Agri. 8.3%, Mnft. 42.0%, Svc. 49.7%)

Module B: General Business Functions

<General Business functions and their technologies>



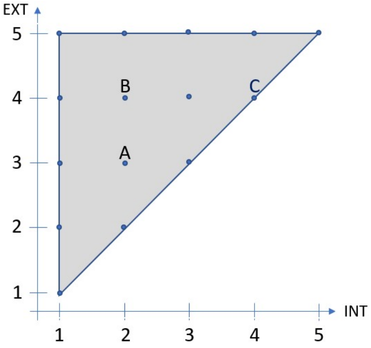
Source: Firm-level Adoption Technology Survey (World Bank, 2022)

II. Measure of technology adoption and main correlates

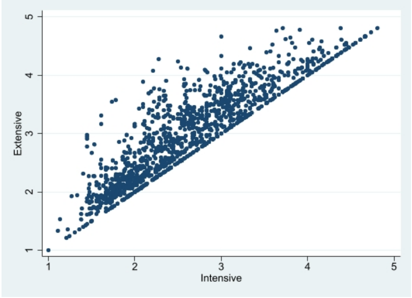
Technology Adoption Measures

- **Intensive margin** (INT, 1 to 5): Most frequently used technology
- **Extensive margin** (EXT, 1 to 5): Highest level of technology
- 1 represents the use of the most basic technology, and 5 is the adoption of frontier technologies.

<Technology Grid>



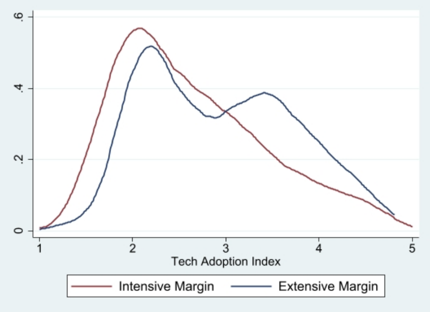
<Scatter plots of INT and EXT>



Considerable heterogeneity in technology adoption

- While some firms are close to the technological frontier, others at the bottom of the distribution rely on the most basic technologies.
- Large firms adopt and use more sophisticated technologies than medium and small firms.

<Distribution of tech index>



<Tech index by firm size>

Characterizing the correlates of technology adoption

Main explanatory variables

- *Managerial quality index*
  $= f($*Family company, Formal incentives, Performance indicators*$)$
- *Management human capital index*
  $= f($*Manager's with college, Manager's experience, Experience in large company, Studied abroad*$)$
- *Innovation and skills index*
  $= f($*Share of college-educated employees, Share of R&D employees, Innovation*$)$

We use unconditional quantile regressions (UQR) to explore what can cause dispersion.

Characterizing the correlates of technology adoption

1. General Business Function - Extensive margin

	Dependent variable: Extensive Margin			
	(1)	(2)	(3)	(4)
	OLS	p(10)	p(50)	p(90)
Log(Employment)	0.206***	0.066***	0.337***	0.203***
Multinational	-0.074	-0.282*	-0.128	0.099
Exporter	0.115*	0.074	0.133	0.116
Managerial quality index	0.385***	0.162**	0.656***	0.402**
Management human capital index	0.499***	0.367***	0.746***	0.410*
Innovation and skills index	0.543***	0.276***	0.851***	0.687***
Interaction with MNEs	0.151**	0.004	0.129	0.478***
Government support	0.004	-0.001	-0.040	0.092
Financial constraints	0.156**	0.138*	0.162	0.121
Constant	2.017***	1.373***	1.567***	3.148***
Region x Sector	Yes	Yes	Yes	Yes
Observations	1,501	1,501	1,501	1,501
R-squared	0.450	0.164	0.344	0.246

Note: ***$p<0.01$, **$p<0.05$, *$p<0.10$.

Characterizing the correlates of technology adoption

2. General Business Function - Intensive margin

	Dependent variable: Intensive Margin			
	(1)	(2)	(3)	(4)
	OLS	p(10)	p(50)	p(90)
Log(Employment)	0.138***	0.065	0.188***	0.095*
Multinational	-0.033	-0.085	-0.051	-0.235
Exporter	0.110	0.029	0.144	0.139
Managerial quality index	0.326***	0.007	0.460***	0.282
Management human capital index	0.437**	0.262	0.280	0.722**
Innovation and skills index	0.468**	-0.178	0.500**	0.825***
Interaction with MNEs	0.067	0.103	0.054	0.210
Government support	0.059	0.214*	0.060	0.017
Financial constraints	0.032	0.031	0.042	-0.028
Constant	-1.381**	-3.122***	-1.648***	0.083
Region x Sector	Yes	Yes	Yes	Yes
Observations	1,240	1,240	1,240	1,240
R-squared	0.184	0.151	0.156	0.165

Note: ***$p<0.01$, **$p<0.05$, *$p<0.10$.

Characterizing the correlates of technology adoption

For the correlates of the technology index at the extensive margin,

- The UQRs indicate a smaller coefficient for firms below the median.
- Firms' size is positively correlated with adopting more advanced technologies across the distribution.
- Interaction with MNEs is only significant for firms at the 90th percentile.

All the three indexes enter significantly with different magnitudes.

- Innovation and skills index coefficient is larger than the other indexes at the 90th quantile.
- Management human capital is larger for firms at the bottom of the distribution.

The results implies an important role of internal factors - human capital of manager, innovation capabilities, part of GVCs.

III. Recent trends of productivity of Korean firms

Korea Enterprise Data (KED)

- KED is a comprehensive repository of corporate information on Korean firms, including financial statements, stock prices, ownership structures, and business performance indicators.
- The data is collected and maintained by Korea's representative credit rating agency (KODAT), which has been gathering raw data from major policy financial institutions.

< Key characteristics of KED>

Sample	1.1 million establishments in Korea (including Conglomerates, SME, Micro firms)
Industry	All sectors, 5digit of KSIC specified
Period	Year 2007 $\sim$ 2021
Infomation included	Balance sheet data, Owner & CEO info Employees, Business counterpart Export & Import, Sales by product, etc.

Estimating the Production Function

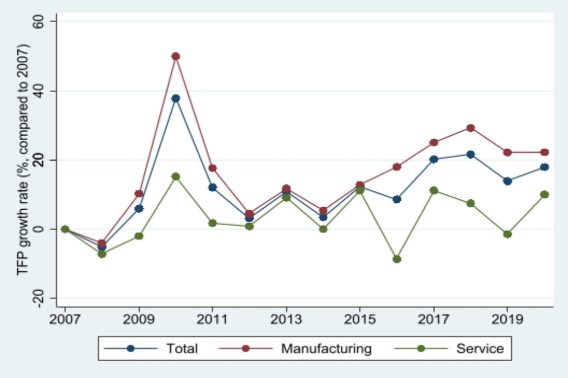
Consider Cobb and Douglas production function in logs for firm i at time t:

$$y_{it} = \alpha + w_{it}\beta + x_{it}\gamma + \omega_{it} + \epsilon_{it} \quad (1)$$

- y_{it}: log value-added (= Sales - Intermediate input cost)
- w_{it}: $1 \times J$ vector of log labor input (= Number of regular employees)
- x_{it}: $1 \times K$ vector of log capital input (= Value of total fixed assets)
- ω_{it}: the unobserved productivity or technical efficiency
- ϵ_{it}: an idiosyncratic output shock distributed as white noise
- Intermediary input = Cost of raw materials and energy.

Estimate Coefficients of the production function of each sector (2 digit of KSIC) by Ackerberg, Caves, and Frazer (ACF, 2015).

Recent trend of productivity growth rate (Employees $\geq$ 50)



- From 2007 to 2010, the TFP growth rate across all industries was relatively high, with an annual average of approximately 12.6%.
- Between 2011 and 2016, the growth rate remained stagnant.
- From 2016 to 2020, there was a renewed growth in the productivity rate, with an annual average of approximately 2.3%.

Recent trend of productivity growth rate (Employees $\geq$ 50)

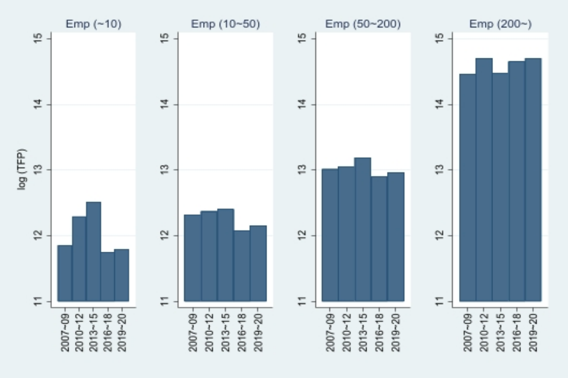
In the manufacturing industry, a trend was similar to that of the overall industry.

- The growth rate was high between 2007 and 2010, followed by a period of stagnation from 2011 to 2015.
- Between 2016 and 2020, there was a resurgence in productivity growth.

The slowdown in productivity growth was more pronounced in the service industry than that in the overall and manufacturing industries.

- After 2010, there was a slowdown in the growth rate of productivity.
- TFP level in 2020 remained at the same level as in 2010.

Recent trend of productivity growth rate by firm size



- The TFP level tends to increase as the size of the company grows larger.
- Firms with over 200 employees demonstrate a higher level of productivity in the period of 2019-20 compared to 2007-09.
- In contrast, firms with 200 or less exhibit either similar or lower productivity levels in 2019-20 than in 2007-09.
- This suggests a widening productivity gap b/w larger and smaller firms.

IV. Relation between technology adoption and productivity

The matching process between FAT and KED data

- Multiple rounds of matching were performed using firm identification information, employing both one-to-one matching and Fuzzy matching.
- As a result, 1,009 out of 1,551 firms in the FAT data were appropriately matched with the KED data.

<FAT + KED matching process>

Matching Round	Linking variables	Comparing variables	**Firm name**	**Phone number**	**Email**	**Address**	Initial Matches	Screening Info.	**Screened Matches**	Matching Round	(FZ) Initial Matches	**(FZ) Screened Matches**	**Total Matches**
(1) M4_1	4	0	Lk	Lk	Lk	Lk	19	Comparing variables + Product descriptions + Employment size + Business starting year	19	(1) F4_1	0	0	19
(2) M3_1	3	1	Lk	Lk	Lk	Compr	6		5	(2) F3_1	0	0	5
(3) M3_2	3	1	Lk	Lk	Compr	Lk	345		336	(3) F3_2	0	0	336
(4) M3_3	3	1	Lk	Compr	Lk	Lk	2		2	(4) F3_3	0	0	2
(5) M3_4	3	1	Compr	Lk	Lk	Lk	0		0	(5) F3_4	0	0	0
(6) M2_1	2	2	Lk	Lk	Compr	Compr	65		63	(6) F2_1	0	0	63
(7) M2_2	2	2	Lk	Compr	Compr	Lk	303		294	(7) F2_2	0	0	294
(8) M2_3	2	2	Compr	Compr	Lk	Lk	0		0	(8) F2_3	0	0	0
(9) M2_4	2	2	Lk	Compr	Lk	Compr	3		3	(9) F2_4	0	0	3
(10) M2_5	2	2	Compr	Lk	Compr	Lk	81		62	(10) F2_5	0	0	62
(11) M2_6	2	2	Compr	Lk	Lk	Compr	2		2	(11) F2_6	0	0	2
(12) M1_1	1	3	Lk	Compr	Compr	Compr	1,087		92	(12) F1_1	26	2	94
(13) M1_2	1	3	Compr	Lk	Compr	Compr	64		34	(13) F1_2	18	2	36
(14) M1_3	1	3	Compr	Compr	Lk	Compr	2		2	(14) F1_3	0	0	2
(15) M1_4	1	3	Compr	Compr	Compr	Lk	1,940		54	(15) F1_4	7	1	55
							Total		968	(16) F0_1	578	18	18
										(17) F0_2	560	5	5
										(17) F0_3	555	2	2
										Total			998
										After Extra work using DART			1009

The relation between productivity and technology adoption

1. Cross-sectional and pooled analysis with **extensive margin**

DV: log(TFP)	Assuming technology has persisted for years			
	(1)	(2)	(3)	(4)
	Y2019	Y2019	Y2016-20	Y2007-20
Extensive margin	0.322***	0.177**	0.245**	0.190***
	(0.076)	(0.078)	(0.036)	(0.024)
log(employment)		0.300***	0.234***	0.224***
		(0.060)	(0.028)	(0.018)
Years of operation		0.009**	0.013***	0.019***
		(0.004)	(0.002)	(0.001)
Constant	9.904***	9.576***	9.486***	9.642***
	(1.016)	(0.998)	(0.480)	(0.297)
Region/Sector/Year	Yes	Yes	Yes	Yes
Observations	801	799	3,895	8,804
R-squared	0.314	0.343	0.372	0.396

Note: Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.10.

The relation between productivity and technology adoption

- Based on the cross-sectional analysis of Model (1) and (2) using 2019 data, a positive correlation was found between a firm's extensive margin and productivity.
- When a firm's extensive margin increases by one level, productivity tends to increase by 38.0% $(= exp(0.322) - 1)$ and 19.4% $(= exp(0.177) - 1)$, respectively.
- Considering the results of the FAT survey indicating a sustained use of the current technology for multiple years, pooled analysis was conducted in Model (3) and (4).
- Model (3) assuming a five-year sustained technology level showed a 27.8% productivity increase, while Model (4) assuming a longer sustained period showed a 20.9% productivity increase.

The relation between productivity and technology adoption

2. Cross-sectional and pooled analysis with **intensive margin**

DV: log(TFP)	Assuming technology has persisted for years			
	(1)	(2)	(3)	(4)
	Y2019	Y2019	Y2016-20	Y2007-20
Intensive margin	0.407***	0.261***	0.305***	0.163***
	(0.083)	(0.085)	(0.039)	(0.025)
log(employment)		0.292***	0.229***	0.232***
		(0.060)	(0.028)	(0.018)
Years of operation		0.009**	0.012***	0.019***
		(0.004)	(0.002)	(0.001)
Constant	9.794***	9.446***	9.434***	9.752***
	(1.010)	(0.995)	(0.479)	(0.296)
Region/Sector/Year	Yes	Yes	Yes	Yes
Observations	801	799	3,895	8,804
R-squared	0.319	0.347	0.375	0.394

Note: Standard errors in parentheses, ***$p<0.01$, **$p<0.05$, *$p<0.10$.

The relation between productivity and technology adoption

3. Panel (FE) analysis using **predicted extensive margin**

DV: log(TFP)	Predicting technology index by			
	(1)	(2)	(3)	(4)
	T.Fixed Ast	Non-crnt Ast	Tg. Ast	Dev Exp
Predicted EXT	0.363***	0.404***	0.259***	0.166***
	(0.008)	(0.008)	(0.009)	(0.011)
log(employment)	0.495***	0.497***	0.491***	0.502***
	(0.001)	(0.001)	(0.001)	(0.001)
log(total asset)	0.015***	0.014***	0.020***	0.078***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	8.826***	8.717***	9.069***	7.870***
	(0.023)	(0.026)	(0.028)	(0.035)
Firm/Year FE	Yes	Yes	Yes	Yes
Observations	1,080,639	1,080,066	1,081,719	588,061
Number of firms	426,903	426,820	426,968	193,643
R-squared	0.317	0.319	0.315	0.391

Note 2. Standard errors in parentheses, ***$p<0.01$, **$p<0.05$, *$p<0.10$.

The relation between productivity and technology adoption

- Since the technology index is only available as of 2019, panel analysis necessitated the creation of a predicted technology variable b/w 2007 and 2020, achieved by utilizing KED's tech-related variables as predictors.
- In Model 1, which utilizes Total fixed asset as a predictor variable, we find a highly significant coefficient of 0.363.
- It suggests that one level increase in the predicted extensive margin is associated with a 43.8% $(= exp(0.363) - 1)$ increase in TFP.
- To get a sense of the magnitude, a one standard deviation change in the predicted extensive margin is associated with a 4.6% $(= exp(0.125 \times 0.363) - 1)$ higher level of TFP.
- Although coefficients' magnitudes change (0.404∼0.166) across the models, the consistent finding that technology adoption positively impacts productivity persists.

The relation between productivity and technology adoption

4. Panel (FE) analysis using **predicted intensive margin**

DV: log(TFP)	Predicting technology index by			
	(1)	(2)	(3)	(4)
	T.Fixed Ast	Non-crnt Ast	Tg. Ast	Dev Exp
Predicted INT	0.354***	0.317***	0.193***	0.112***
	(0.008)	(0.008)	(0.010)	(0.010)
log(employment)	0.489***	0.493***	0.485***	0.499***
	(0.001)	(0.001)	(0.001)	(0.001)
log(total asset)	0.0187***	0.0178***	0.0236***	0.0801***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	8.936***	9.031***	9.287***	8.064***
	(0.023)	(0.024)	(0.027)	(0.030)
Firm/Year FE	Yes	Yes	Yes	Yes
Observations	1,082,457	1,081,557	1,083,021	588,262
Number of firms	427,022	426,991	427,053	193,663
R-squared	0.314	0.316	0.311	0.388

Note 2. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.10.

V. Conclusion

Summary

- Using the Korea FAT survey (Cirera et al. (2020)), we develop new measures of technology adoption and correlates them with productivity.
- Results reveal heterogeneity in technology adoption, with larger firms adopting more sophisticated technologies than smaller ones.
- Managerial quality, management human capital, innovation and skills are significant factors in technology adoption.
- Productivity growth rates were high from 2007-2010, stagnant from 2011-2016, and renewed from 2016-2020, with a widening productivity gap between larger and smaller firms.
- Technology adoption is positively correlated with productivity, with a one-level increase in technology adoption leading to an increase in productivity of 38.0% in cross-sectional analysis, 27.8% in pooled analysis, and 43.8% in panel analysis.

Policy implications

Government policies should promote and encourage small businesses to adopt advanced technology, as the technology-productivity gap between small and large businesses is substantial and technology adoption tends to have a significant positive impact on productivity.

1. The FAT survey suggests firms rely more on other firms than industry associations, public technology transfer services as primary sources of information for purchasing decisions.

   Encouraging participation in innovation hubs and clusters can facilitate communication and information exchange among companies.

Policy implications

2. To ensure the dissemination of formal incentives and performance indicators that make up the Managerial Quality Index, continuous consulting services should be provided to support firms in receiving ongoing guidance on business operations.
3. Since the experience of employees in multinational and large companies, which are components of the Management Human Capital Index, tend to enhance technology adoption, efforts should be made to invest in the education and job training of managers and employees, as well as to activate knowledge and technology sharing between large and small businesses.

Policy implications

4. Brynjolfsson et al. (2019) emphasized that the effective harnessing of new technologies requires significant time due to various co-inventions, obstacles, and adjustments.

   To ensure a seamless integration of new and existing technologies and the adoption of necessary technologies, governments should provide continuous and comprehensive support systems rather than one-time technological assistance.