Policy Research Working Paper 9567

Firm-Level Technology Adoption in Vietnam

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WORLD BANK GROUP
Finance, Competitiveness and Innovation Global Practice
March 2021

Abstract

This paper describes the results of a new firm survey to measure technology use and adoption implemented prior to the COVID-19 pandemic in Vietnam. It analyzes the use and adoption of technology among Vietnamese firms and identifies some of the key barriers to adoption and diffusion. The analysis offers new and important stylized facts on firm-level use of technologies. First, although access to the internet is almost universal in Vietnam, firms had low digital readiness to face the COVID-19 pandemic; and the share of establishments with their own website, social media, and cloud computing is still small. Second, the use of Industry 4.0 technologies is incipient. Third, the technology gap with the use of frontier technologies in some general business functions, such as quality control, production planning, sales, and sourcing and procurement, is large. Fourth, the manufacturing sector faces the largest technological gap, larger than services and agricultural firms. The analysis of the main barriers and drivers to technology adoption and use shows the importance of good management quality for technology adoption, and that there is a technology premium associated with exporting activities. Finally, the analysis also shows that firms are largely unaware of the available public policy support for technology upgrading.

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JEL Codes: D2, E23, L23, O10, O40

Keywords: Technology, Firms, Vietnam, Adoption and diffusion, Industry 4.0

*We would like to thank the General Statistical Office of Vietnam (GSO) for their partnership in data collection and implementation of this project, and in particular the head of GSO's industrial statistics department Mr. Pham Dinh Thuy. We also thank Hoang Linh Vu for field support during data collection; and Asya Akhlaque, Denis Medvedev, Zafer Mustafaoglu, Brian Mtonya, Lien Anh Pham, Shawn Tan and Trang Thu Tran for comments at different stages of the paper. Thanks to Hoa Chau Nguyen for overall administrative support. Financial support from the Korea World Bank Group Partnership Facility (KWPF) is gratefully acknowledged.

1 Introduction

In the span of only 30 years, Vietnam has moved from one of the world's poorest nations in the late 1980s to a lower-middle-income country. The economy has expanded at an annual average growth rate of nearly 7 percent since 1988, leading to an almost five-fold increase in its per capita income and a continuing decline in poverty. This growth *miracle* has been associated to a large extent with trade openness and export-orientation based on its comparative advantage in low-cost labor-intensive manufacturing. Vietnam enjoyed the growth benefits of moving a large pool of unskilled workers from subsistence activities to more modern manufacturing or services occupations; the country played to its strengths by focusing on labor-intensive production (wearing apparel and leather and footwear) and agriculture.

However, there are indications that this formidable performance is under threat and it may be difficult to sustain. First, declining productivity growth poses a risk to the country's aspirations of ensuring a prosperous life to its population. Maintaining a fast growth pace will depend on the ability to maintain productivity growth and move towards more sophisticated activities and technologies, build innovation capacity (World Bank, 2016) and raise labor productivity to create more and better jobs. Second, Vietnam is facing several challenges that threaten its economic development model. Increased productivity with changing demography implies that the low labor cost model cannot be sustained. The instability of the global trade regime with arising new trade disputes also menaces the export-led model. Third, a new industrial revolution, Industry 4.0, is increasing the potential for re-shoring of production. More flexible manufacturing and proximity to clients implies a risk of reversing the offshoring of some activities, especially in the production of wearing apparel and electronics that benefited the flow of FDI to the country. Fourth, the COVID-19 pandemic and other future pandemics threaten growth in Vietnam, and stress the importance of digital preparedness to keep more flexible business operations to face potential lockdowns, such as online sales, integrated digital systems that facilitate home-based work and automated production processes that minimize social contact and help in implementing health protocols.

A critical response to address these challenges is technology upgrading. Adopting and using more sophisticated technologies can accelerate productivity growth and reduce the technology gap with developed economies. Digital readiness can help smooth the economic shocks from current and future pandemics. But the adoption of more sophisticated technologies in Vietnam will depend on effective policies that eliminate a number of barriers that produce a widening gap between laggard firms and those with more advanced technologies. Eliminating these barriers and spurring technology upgrading can have a significant impact on Vietnam's trajectory to becoming a high-income country.[1]

Designing effective innovation and technology policies requires eliminating some critical policy and institutional barriers that are constraining their effectiveness (see World Bank (2020) for a review of the policy challenges in Vietnam for spurring innovation). Yet, without good measures in the use and adoption of technology at the firm level, it is not possible to determine what are the main technology gaps and what are the obstacles that firms face when trying to adopt more advanced methods of production. The objective of this paper is to shed some light on this issue and provide a granular measure of existing technology gaps in Vietnam. We do so by describing the results of the "Firm-level Adoption of Technology" (FAT) survey.

The Firm-level Adoption of Technology (FAT) survey, developed by Cirera, Comin, and Cruz (2020), is an innovative tool to measure at a very granular level the technology use at the firm-level. The survey implemented in Vietnam includes a nationally representative random sample of about 1,500 firms with 5 or more employees from the latest establishment census.[2] The survey identifies the purpose of technologies adopted by the firm, through general and sector specific business functions, and then for each business function it measures the technologies used (*extensive margin*) and the most frequently used (*intensive margin*) (see Appendix A for a detailed description). This allows a very granular measure of technology adoption and use. To our knowledge, beyond specific case studies and the attempt to measure general purpose technologies, there have been very few studies to systematically measure adoption using firm level questionnaires harmonized across countries.

The paper analyzes the adoption of technologies at the firm-level in Vietnam through three key angles: (1) Standard measures of technologies associated to different technology revolutions; (2) Technologies applied to general business support functions; and (3) Sector specific technologies. The standard firm-level measures of technologies refer to "traditional" measures of general-purpose technology (GPT) adoption, which enable firms to apply more technologies towards specific tasks. It includes the access and usage of GPTs such as electricity, phone, computers, internet, and social networks. To measure the use for specific tasks we define general business functions (GBF) as those tasks applied to any firm, regardless of the industries they are in; such as business administration, production planning, sales, and payments methods. Given that production processes differ by sector, we define sector

[1]Differences in the timing of adoption of new technologies can account for up to a quarter of per capita income disparities across countries (Comin and Hobijn, 2010) and for up to 80% when also taking into account how long it takes these technologies to become widely adopted (Comin and Mestieri, 2014).

[2]The FAT survey in Vietnam was implemented by the General Statistics Office (GSO) of Vietnam, in collaboration with the World Bank, using a representative random sample based on the latest establishment census available, conducted by the GSO in 2018.

specific business function (SSBF) as those tasks applied for business functions that are industry specific (e.g. land preparation in agriculture industries, or input testing in the food processing industry). For each type of function, we measure the technology used.

The paper is structured as follows. Section 2 describes the level of adoption using standard measures of general-purpose technologies, such as access to electricity, computers or internet without identifying the specific purpose of use. Section 3 describes a new set of measures of technologies developed using the survey. Section 4 analyzes the level of technology adoption and use for general business functions. Section 5 analyzes the level of technology adoption and use for sector specific technologies. Sections 6 describes some of the key barriers for technology adoption in Vietnam, while section 7 analyzes the relationship between technology adoption and employment. The last section concludes.

2 General Purpose Technology Use: From Industry 2.0 to Industry 4.0

Standard measures of general purpose technologies (GPTs) can be linked to different stages of industrial revolutions, following the reference period in which these technologies became available. We organize the information on adoption and use of GPTs in three types according to the period when these technologies were originated and production processes changed: Industry 2.0, 3.0, and 4.0. Industry 2.0 encompasses electricity and generators, which are technologies from the 1880s. Industry 3.0 refers to the ICT revolution, including mobile phone, computer, and Internet. These technologies became available over the 1970-1980 period but diffused at different speeds in developing countries.[3] Industry 4.0 refers to technologies that in most cases have some digital component, but higher level of autonomy and connection of information across different devices and machines to perform tasks. Among the technologies usually associated with Industry 4.0 are the Internet of Things (IoT), Big data analytics and artificial intelligence, 3D printing, advanced robotics or cloud computing.[4]

2.1 Industry 2.0: Electricity

The availability and quality of electricity and telecommunications services can be decisive in a firm's decision to adopt a new technology. Table 1 shows the descriptive statistics

[3] Comin and Mestieri (2018a) show the reference year of invention for these technologies: electricity (1882), PCs (1973), cellphones (1973), and internet (1983).

[4] Nayyar and Hallward-Driemeier (2018) provide further discussion on the emergence of Industry 4.0. Although some of these technologies, such as AI were already available, since the 1960s they have been increasingly available in recent years.

of access to electricity, power outages, and alternative source of electricity. The first two columns show the average and standard deviation. The descriptive statistics are further divided by size groups and sectors. Three firm size groups are defined by the number of employees: small (5-19), medium (20-99), and large (100+). Although access to electricity is widely available in the country (99.9%), power outages are a significant obstacle; 75% of establishments in Vietnam face frequent power outages. Differences across size groups are small, while manufacturing companies are more affected.

Table 1: Access and Quality of Electricity

Technology	**Mean**	**Std. Dev.**	**Small**	**Medium**	**Large**	**Agric.**	**Manufac.**	**Services**
Having Electricity	99,99%	0,01	99,98%	100%	100%	97,68%	100%	100%
Power Outage	74,83%	0,43	73,93%	78,30%	77,59%	78,04%	87,27%	70,52%
Having Generator	18,67%	0,39	14,54%	29,76%	44,28%	32,32%	23,65%	16,82%
Energy: Solar Power	0,14%	0,04	0,04%	0,05%	0,72%	2,39%	0,04%	0,15%
Energy: Fuel	91,27%	0,28	92,31%	90,87%	87,38%	87,28%	90,55%	91,69%
Energy: Wind Power	0%	0%	0%	0%	0%	0%	0%	0%

As a result of experiencing power outages, 19% of establishments have their own generator; 44% of large firms in Vietnam have generators, a larger share than medium (15%) and small (30%). In terms of sectors, the share is larger for agriculture (32%) than manufacturing (24%) and services (17%), which is likely to be explained by agricultural establishments being located in more isolated areas. Among those firms that have or share generators, the large majority relies on fuel, used in 91% of establishments, and the use of renewable energy is marginal and almost non-existent. Although all regions have access to electricity, power outages are more frequent in the Northeast, Mekong and Red River Deltas, and North Central areas. Table 2 shows the access to electricity and use of alternative sources of energy by regions. For instance, 97% of firms in the North Central region face outages, compared to 65% of the establishments in Hanoi. These differences have a clear and positive association with the use of generators.

Table 2: Access and Quality of Electricity by Region

Region	**Electricity**	**Power Outage**	**Having Generator**	**Solar Power**	**Fuel**
Red River Delta (without Hanoi)	100,0%	91,8%	26,5%	0%	96,7%
Northeast	100,0%	90,6%	29,9%	0%	99,4%
North Central	100,0%	96,7%	31,3%	1,2%	90,9%
Central Highlands	98,8%	76,1%	30,3%	1,3%	98,2%
Southeast (without Ho Chi Minh)	100,0%	87,6%	26,3%	0%	83,0%
Mekong River Delta	100,0%	96,8%	13,0%	0%	98,4%
Hanoi	100,0%	64,8%	18,3%	0%	91,7%
Ho Chi Minh City	100,0%	74,0%	11,4%	0,1%	90,4%

2.2 Industry 3.0: ICT

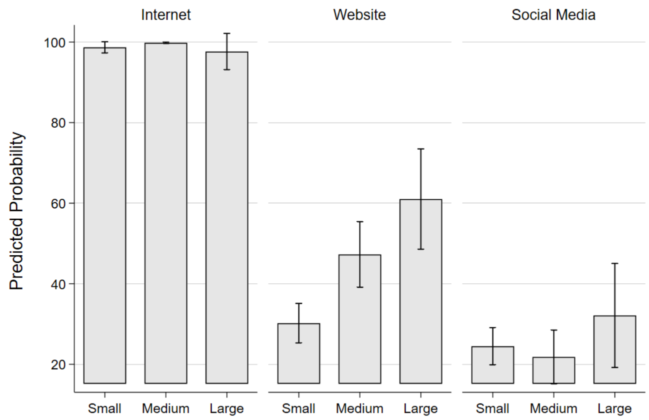
Most firms have access to basic technologies such as mobile phone and computer. Table 3 shows the summary statistics on general purpose technologies. About 90%-94% of firms use a telephone for business purposes, while on average 88% use mobile phones, with the share increasing with firm size. The same pattern is observed in the use of computers and smartphones, with a clear and positive association between access to basic technologies and firm size. The divergence in the adoption of computers and smartphones or tablets for business purposes is also clearer when considering the intensive margin. Larger firms have a significantly larger number of devices, which is consistent with their scale. On average, small firms have about 5 computers, while medium firms have about 11 computers per firm, and large firms have about 44 computers, either desktop or laptop, per firm.

Table 3: Access to Basic Digital Technologies

Technology	**Mean**	**Std. Dev.**	**Small**	**Medium**	**Large**
Having Telephone	90,4%	0,29	90,2%	90,2%	94,0%
Having Mobile Phone	88,1%	0,32	89,9%	87,0%	70,7%
Having Computer	99,8%	0,05	99,7%	100,0%	100,0%
Having Smartphone	60,9%	0,49	62,1%	58,3%	54,2%
Having Internet	99,7%	0,05	99,7%	99,9%	98,8%
Type: Dial Up Internet	3,7%	0,19	4,2%	2,7%	0,6%
Type: DSL Internet	92,7%	0,26	92,9%	91,2%	94,1%
Type: Wireless Internet	1,9%	0,14	1,5%	3,6%	1,3%
Type: BPL Internet	0,7%	0,08	0,5%	1,0%	2,0%
Acquisition of software	1,1%	0,10	0,9%	1,5%	2,1%
Number of Telephones	1,99	2,96	1,53	2,51	5,91
Number of Mobile Phones	3,82	9,18	3,04	6,16	6,43
Number of Computer	8,93	22,20	5,43	10,99	43,91
Number of Smartphone	2,80	11,03	2,00	4,54	7,11

Practically all establishments have access to the internet, with 93% using DSL connection. On the other hand, there is a clear and positive association between having their own website and social media and firm's size (see Figure 1). Only about 25% of firms in Vietnam make use of social media for business. This incipient use of digital platforms and tools indicates lack of readiness for the adjustment required by the COVID-19 pandemic.

Figure 1: Share of Firms with Internet, Own Website, and Social Media



Note: Figure shows the predicted probability of firms with internet, own website, and social media on size from the Probit regressions, while controlling for sector and region. All estimates are weighted by sampling and country weights.

2.3 Industry 4.0

Adoption of key technologies in Industry 4.0 is still very incipient in Vietnam. As Figure 2 shows, only 6.9% of firms make use of cloud computing for business tasks. Also, only 1.5% use Big Data or AI for marketing purposes, and when it comes to fabrication, advanced methods for manufacturing are used by only 6.1% of firms and robots by 5.9% of firms. Low rates of adoption of Industry 4.0 technologies are also found in sector specific technologies. In agriculture, only 7.1% of firms use precision agriculture (IoT) technologies, while only 1.8% of firms in manufacturing use additive manufacturing technologies such as 3D printing. Overall, these results suggest a large gap in adoption of Industry 4.0 technologies.

Figure 2: Share of Firms Adopting Industry 4.0 Technologies

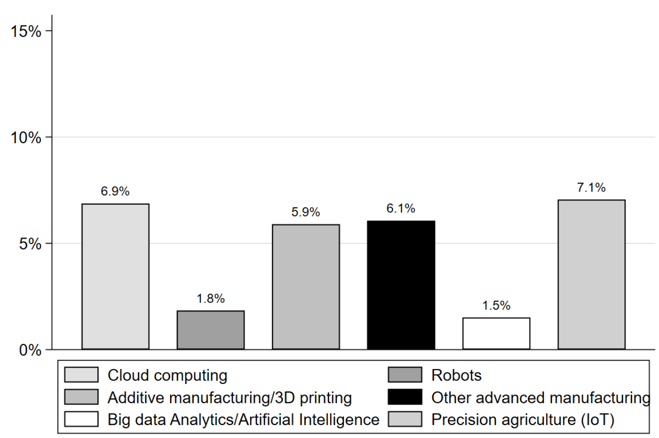
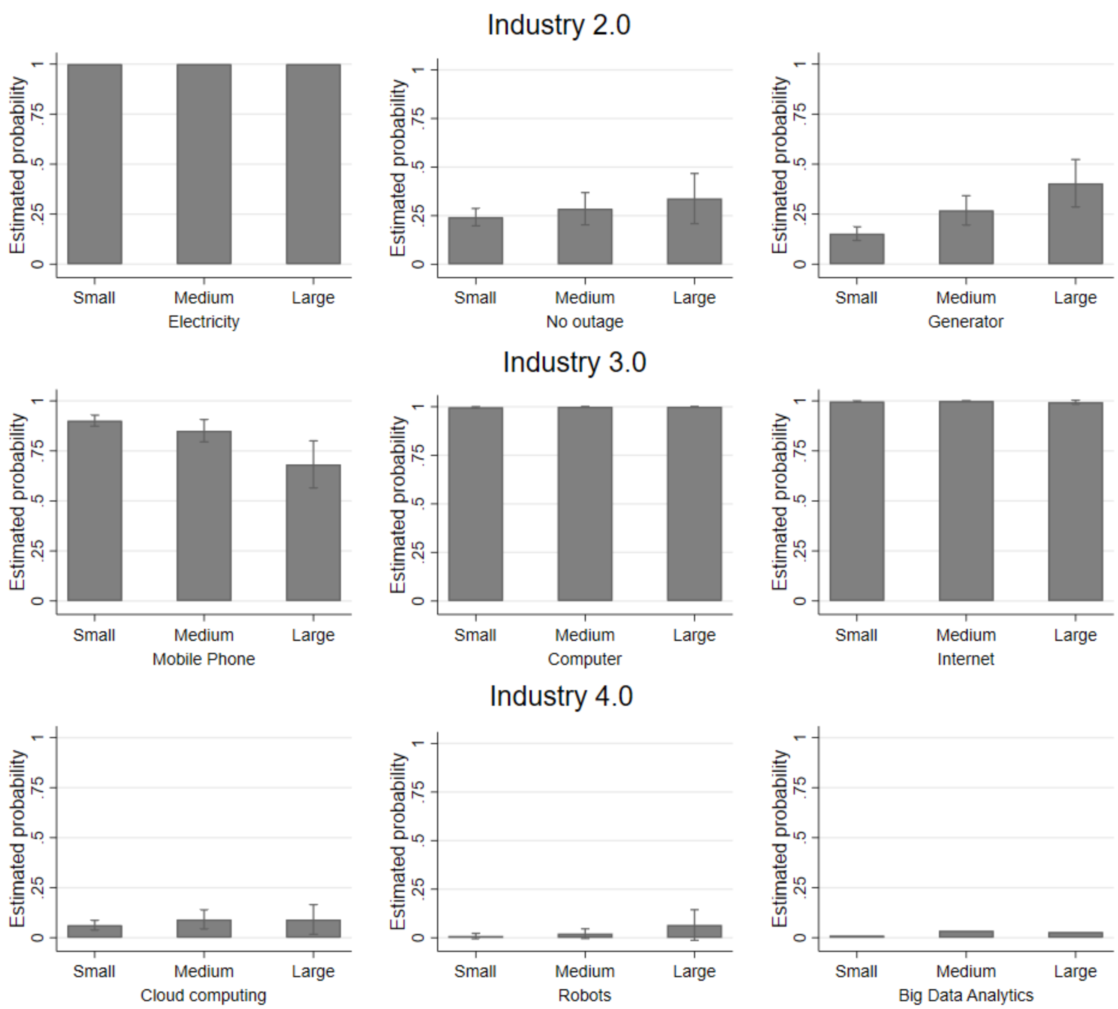


Figure 3 summarizes the likelihood of firms in different size groups to have access to general-purpose technologies (GPTs) in Vietnam, from industry 2.0 to industry 4.0. The results, controlling for sector and region fixed effects, show that despite the universal access to electricity, the likelihood of having high quality access (with no outage) is still relatively low (around 25%). Electricity and especially reliable electricity is an enabling technology of all other technologies. In relation to Industry 3.0 there is almost universal access to mobile, computers, and Internet. Yet, the likelihood of having its own website and use social media for the business is still low. Finally, use of industry 4.0 technologies is very incipient.

Figure 3: Summary of General Purpose Technology Adoption and Use in Vietnam



Note: Figure shows the predicted probability of adoption by size with confidence intervals from the Probit regressions controlling for size, sector, and region. All estimates are weighted by sampling and country weights.

Although these indicators provide a general picture of the adoption of a few GPTs, we continue to lack understanding about the use of these technologies in different functions and production processes. What are the business functions for which those firms are using computers or Internet? How are these technologies being used for production? We explore these issues in the next section.

3 New Measures of Technology Adoption and Use: Linking Technologies to Business Functions

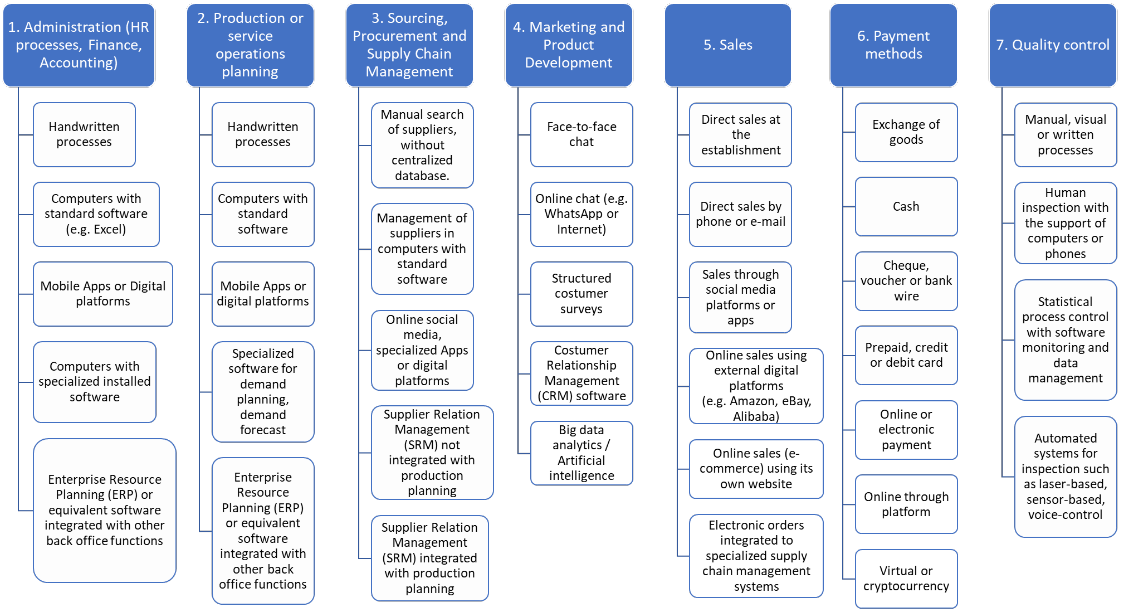
To identify the purpose for which a technology is used by the firm, we link the information on the use of technology with specific business functions. We follow the methodology proposed by Cirera, Comin, and Cruz (2020) and split business functions in two groups: i) General Business Functions, which are common tasks that apply to all firms (e.g. business administration, sales, payment, quality control); and ii) Sector Specific Business Functions, which vary across each sector and are usually more related to core production functions.

The General Business Support Functions (GBFs) are commonly available across all firms, irrespective of the industries they are in. Therefore, they provide good comparison across firms, sectors and countries. The FAT survey identifies the purpose for which a given technology is being applied. Figure 4 describes the key GBFs covered by the survey and the technologies associated with them: 1) Business Administration; 2) Production Planning; 3) Sourcing and Procurement; 4) Marketing and Customer Information; 5) Sales; 6) Methods of Payment; and 7) Quality Control. The technologies associated with most business functions follow a ladder of sophistication that goes from the most basic (e.g. handwritten process for production planning) to the most sophisticated level (e.g. Enterprise Resource Planning (ERP) systems for production planning).

The Sector Specific Business Functions (SSBFs) are tasks that are associated with the core production or service provision activity and varies across sector. The FAT survey in Vietnam has the specific sets of questionnaires towards 9 sectors: i) Agriculture (Crops, Fruits, and Vegetables); ii) Agriculture (livestock); iii) Food Processing; iv) Wearing apparel; v) Retail and Wholesale; vi) Land Transportation; vii) Finance; and viii) Health. Among those, the survey was stratified for and provides a representative sample for firms in agriculture, food processing, wearing apparel, and retail.

The survey asks information on more than 300 technologies associated to almost 50 business functions. To analyze the level of technology adoption and use in a more systematic way, we convert the information for each business function into a technology index. The index, described by Cirera et al. (2020), varies between 1 and 5, where 1 stands for the most

Figure 4: General Business Functions



basic level of technology been used and 5 reflects the most sophisticated level been used. With the help of experts for each industry, we assigned a rank to the technologies in each business function according to their sophistication.

We construct two basic indices: i) The extensive margin, and ii) The intensive margin. The extensive margin identifies if the firm is adopting a technology to perform a given task. This is based on a yes or no question for the adoption of a technology to perform a specific task. The intensive margin is based on the most used technology to perform this task.[5]

Table 4 compare the different technology indices for Vietnam, Senegal, and the State of Ceará in Brazil.[6] Although Vietnam's indices are above those of Senegal and close to those of Ceará, the results clearly show that firms in Vietnam are far from the frontier in the

[5]For example, if a firm performs administrative processes associated with HR, financing, and accounting through handwritten processes and computers with standard software, the extensive margin index equals 2. In this case, the maximum value (5) is attributed to a firm using the Enterprise Resource Planning (ERP) system, which was identified as the technological frontier to perform this task. Because this firm uses two different methods to perform this task, we ask what is the most frequently method. If handwritten, the intensive margin index equals (1). If computer with standard software, the intensive margin equals (2). Figure B2 in the appendix describes an example of the index in the extensive and intensive margins for one general business function (left) and one sector specific function (right), following a vertical quality ladder.

[6]At the time of this report, in addition to Vietnam, only Senegal and the State of Ceará have been completed. Bangladesh is also completed but only includes some manufacturing sectors. Malawi, Jamaica and the Philippines are on the field and tge Republic of Korea and Kenya will be implemented shortly.

adoption of technologies.[7] The gap with respect to Ceará[8] varies from 0.6 (15% relative gap to Brazil) on the GBFs extensive margin to only 0.12 to the SSBFs intensive margin (just 3% relative gap to Brazil). Yet, the gap with respect to the frontier is large, particular for sector specific business functions. As expected, the distance to the frontier is higher at the intensive margin since a firm can always use a more sophisticated technology not necessarily more intensively.

Table 4: Cross-Country Differences in Technology

	General Business Function		Specific Business Function	
	Extensive	Intensive	Extensive	Intensive
Average	2.67	1.90	2.30	1.66
Ceará (Brazil)	3.35	2.49	2.75	1.92
Vietnam	2.75	1.92	2.55	1.80
Senegal	1.92	1.29	1.59	1.27
Gap: BR - VT	0.60	0.57	0.20	0.12
Relative Gap**	15%	14%	5%	3%

Source: Cirera et al. (2020)

Note: Average is the average of Brazil, Vietnam, and Senegal. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 ((Brazil - Senegal)/Maximum Gap(4)).Technology measures are weighted by the sampling weights.

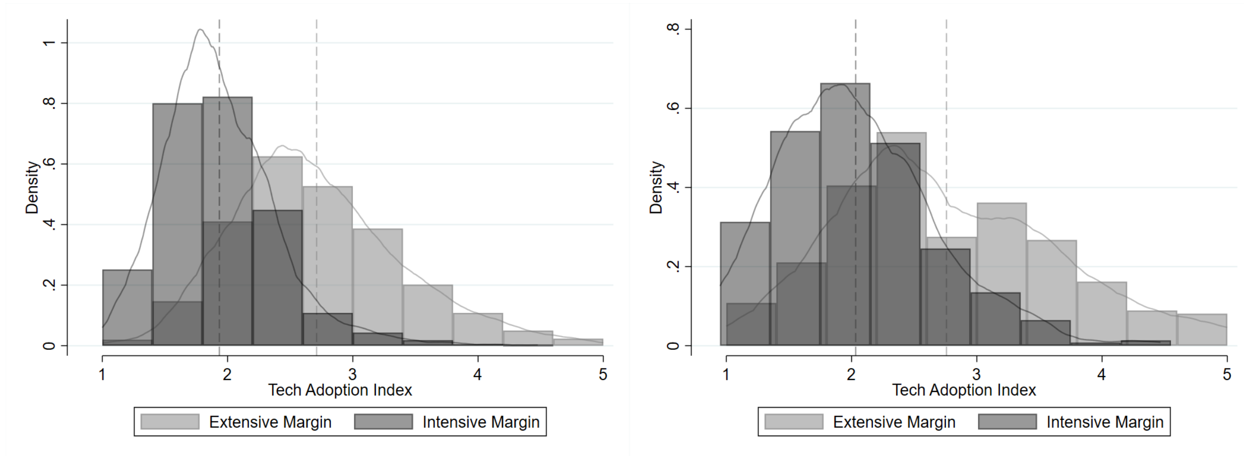
Figure 5 presents the distribution of the technology index for GBFs and SSBFs in Vietnam across firms. First, it is clear by the right-skewed distribution that most firms sill rely on very basic technologies. Also, it is evident that even though some firms are making use of more advanced technologies at the extensive margin, the intensity in which these technologies are used remains very low in Vietnam. Also, there is higher variance and heterogeneity in SSBFs technology sophistication.

Table 5 shows the extent of regional heterogeneity in technology sophistication. Hanoi appears as the region with more sophisticated use of technologies among its firms for general business functions and the Central Highlands for sector specific business functions. Interestingly, comparing the relative gap across regions, it is much smaller than the gap between countries, both between Vietnam and Senegal and between Brazil and Vietnam, although only for GBFs. The regional relative gap is larger for GBFs at the extensive margin.

[7]The index oscillates between 1 for manual technologies and 5 for frontier technologies, with 3 as the middle index.

[8]Ceará is located in the Northeast Region and is one of the country's most populous and poorest states. In 2017, GDP in the state was US$101 billion, with a population of 8.8 million. The state is ranked 11th in terms of GDP and 23rd for GDP per capita (accounting for approximately 2% of the national GDP). The agriculture and livestock sector accounts for 5.76% of GDP, followed by industry, 22.55%, and services, 71.69%.

Figure 5: Distribution of Technology Adoption and Use Across Firms



(a) General business function (b) Sector-specific business function

Note: Lines represent Kernel densities. Vertical dotted lines show the averages.

Table 5: Technology use by region

	GBF Ext	**GBF Int**	**SBF Ext**	**SBF Int**
Red River Delta (without Hanoi)	2.76	1.96	2.48	1.84
Northeast	2.42	1.77	2.42	1.95
North Central	2.46	1.78	2.20	1.73
Central Highlands	2.53	1.79	2.63	2.08
Southeast (without Ho Chi Minh)	2.74	1.86	2.43	1.66
Mekong River Delta	2.42	1.81	2.27	1.80
Hanoi	2.88	1.96	2.57	1.96
Ho Chi Minh City	2.67	1.91	2.35	1.89
Gap: max-min	0.46	0.19	0.43	0.42
Relative gap	12%	5%	11%	11%

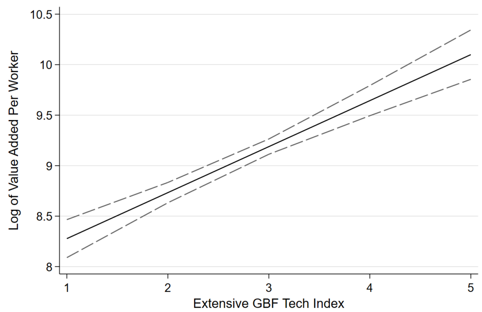
Note: Relative gap is (max-min)/Maximum Gap(4).

Easterly and Levine (2001), Comin and Hobijn (2010) and Comin and Mestieri (2018b) show that technology is a key driver of productivity differences across countries. Kwon and Stoneman (1995) show this relationship for firms in manufacture and an extensive literature in agriculture has shown the impact of technology adoption on farm productivity. Using our data we observe a positive and statistically significant correlation between technology adoption and productivity – measured by value added per worker. Those firms with higher level of technology measured by the index we propose also have better performance in terms of labor productivity (Figure 6).[9]As expected, the relationship is stronger at the intensive

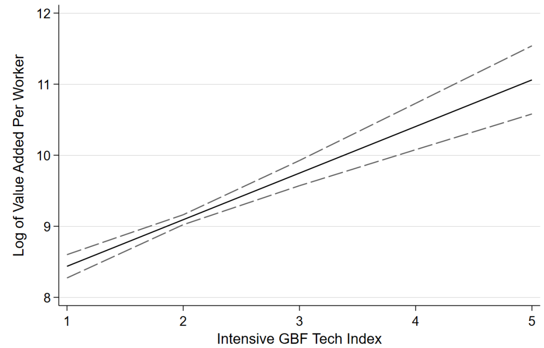
[9]The elasticity of the technology index with respect to value added per worker is 0.77 and 0.74 for the

margin, since this measures the most intensively used technology. While these results do not suggest any causal relationship between technology and performance, they are consistent with previous literature. Adopting better technology pays off.

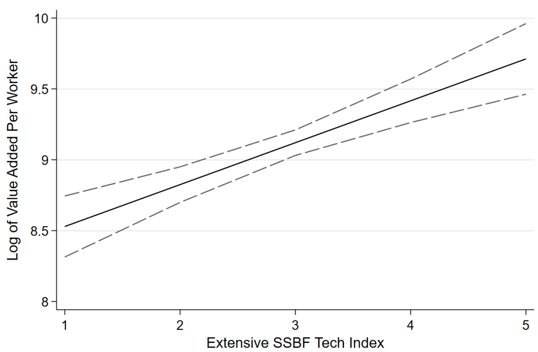
Figure 6: Technology Index and Value Added per Worker



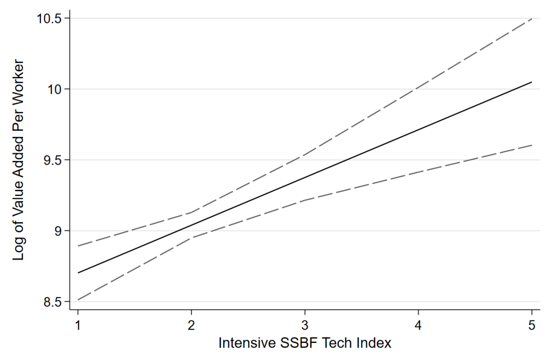
(a) Correlation between extensive GBF index and labor productivity



(b) Correlation between intensive GBF index and labor productivity



(c) Correlation between extensive SSBF index and labor productivity



(d) Correlation between intensive SSBF index and labor productivity

Note: Figure shows linear fit and 95% confidence intervals from regressions. Log of value added per worker is regressed on the log of each technology measure, while controlling for sector, size, and regions.

4 Technology Use in General Business Functions (GBF)

General business functions (GBFs) are commonly needed business functions across all firms, irrespective of the industries they are in, and therefore the GBF technology index is a good comparator across firms, sectors and countries. As described above we create an index for both the extensive and intensive margin that summarizes the level of adoption and use for

extensive and intensive margin GBFs, respectively. Table C2 in the appendix provides the full results for these estimates.

7 business functions.[10]

4.1 Technology use at the intensive and extensive margins

The GBF index varies from 2.7 to 3.1 in the extensive margin and from 1.9 to 2.2 in the intensive margin, suggesting that firms still rely on not fully digitized technologies to implement most tasks in the firm. Figure 7 shows the average indices for the intensive and extensive margin by size, with the black and red vertical lines indicating the average and median index for the whole economy, respectively. Although there is evidence of a positive relationship between both indexes and firm's size, the difference isn't large. Yet, it is clear that even large firms show a significant gap compared to the frontier (5 would be frontier technology in all GBFs).

Figure 7: GBFs: Extensive and Intensive Margin in Vietnam by Firm Size

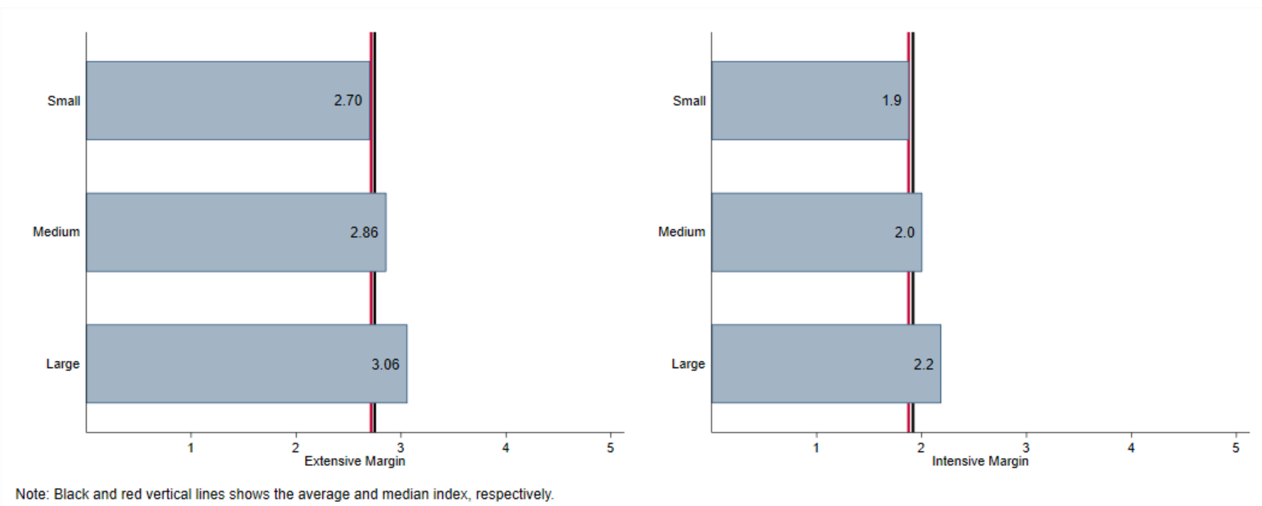
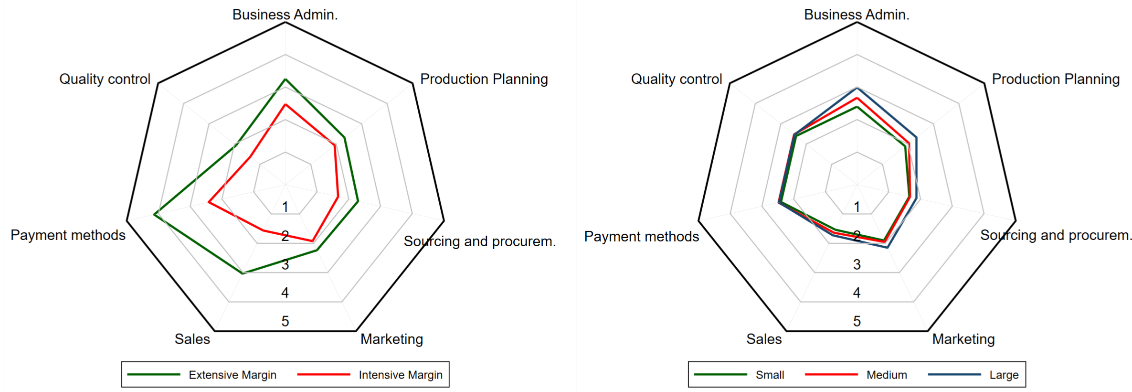


Figure 8 details the index for each business function, suggesting a series of interesting facts about the Vietnamese economy. First, there is a significantly large gap between the extensive and intensive margin for Payment Methods and Sales. The large difference in terms of extensive and intensive indexes suggests that even though firms are adopting more sophisticated technologies, the use of these technologies is still limited and the most often used technologies are usually the more basic ones. Differences across size groups are small, irrespective of business function. Also, Business Administration and Payment Methods are the GBFs with the larger index for extensive and intensive index, yet with a large gap with respect to the frontier.

[10] We also measure a fabrication function for manufacturing, which we exclude here to guarantee the comparability across sectors.

Figure 8: General Business Functions in Vietnam



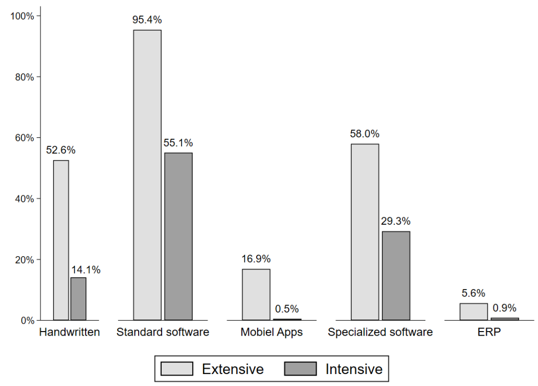
(a) Extensive and intensive SSBF

(b) Intensive SSBF by size group

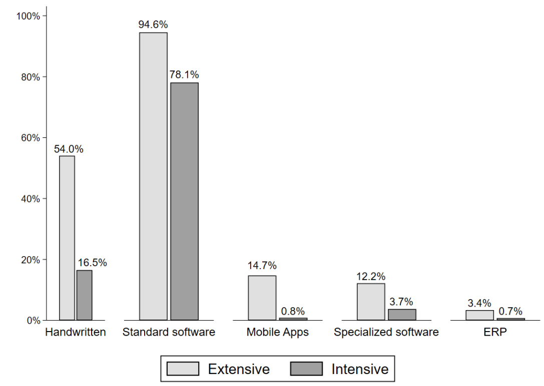
Note: Each line represents the index average across firms for each business function.

For most business functions technology use is concentrated in low sophistication technologies with the use of manual methods or computers but without specialized software. In the intensive margin, only 5.6% of the establishments use ERP and 4.9% use CRM as the most used method for Business Administration and Customer Information. Figure 9 goes on and details the extensive and intensive margin for some business functions. It is clear, for instance, that most firms still relying on sales at the establishment's premises (33%) and by phone, email, or representatives (62.2%) in the intensive margin. As seen above, even though 26% of companies use Social Media, only 1.7% have stated that this is the most used sales method. Similarly, despite firms using some more advanced payment methods, such as online bank, most payments are made using check or bank wire. Customer information technologies are very limited in Vietnam, with most firms relying on face-to-face and online chat as their main source of information. For Business Administration, only 5.6% of firms use ERP, while 14% still rely on handwritten as the most used technology. These results show lack of readiness for the challenges of the pandemic and the associated shock. Lack of integrated digital systems makes home-based work difficult to implement. Similarly, low online sales magnify the negative effect of lockdown measures.

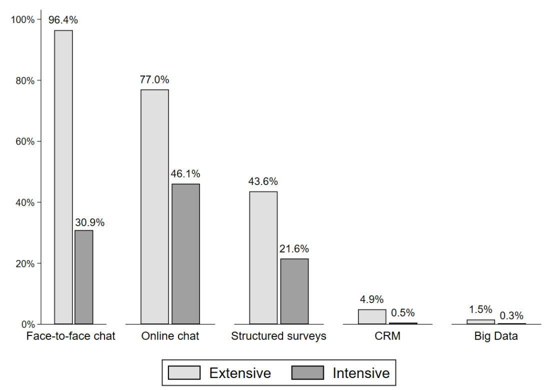
Figure 9: Share of Firms Using Technologies Applied to General Business Functions



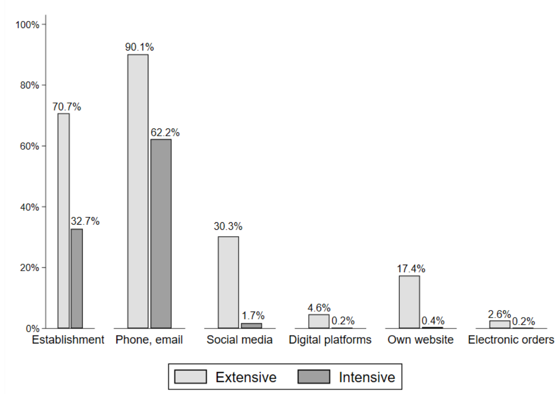
(a) Business administration processes related to account, finance, and HR



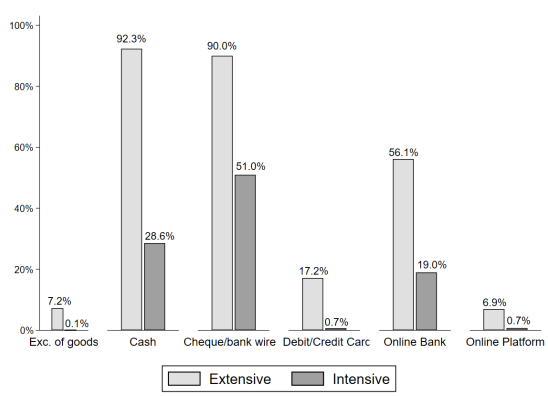
(b) Production or service operations planning



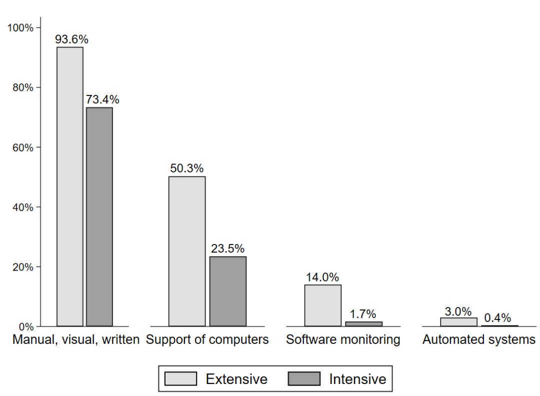
(c) Customer information for marketing and product development



(d) Sales methods



(e) Payment methods



(f) Quality control inspection

4.2 Comparing technology use by sector

Technology use differences across sectors on aggregate are marginal at the extensive margin, but when it comes to the most intensively use technology for GBFs the services sector uses more sophisticated technology. Table 6 shows the difference in technology adoption indices by aggregated sector for the average level of adoption - average between general and sector specific business functions - general business functions only and sector specific business function only (see next section); for both the intensive and extensive margin. The services sector has a higher index when it comes to general business functions at both the intensive and extensive margin. This contrasts with existing biases against this sector in terms of support for technology policies.

Table 6: Cross-sector Differences in Technology

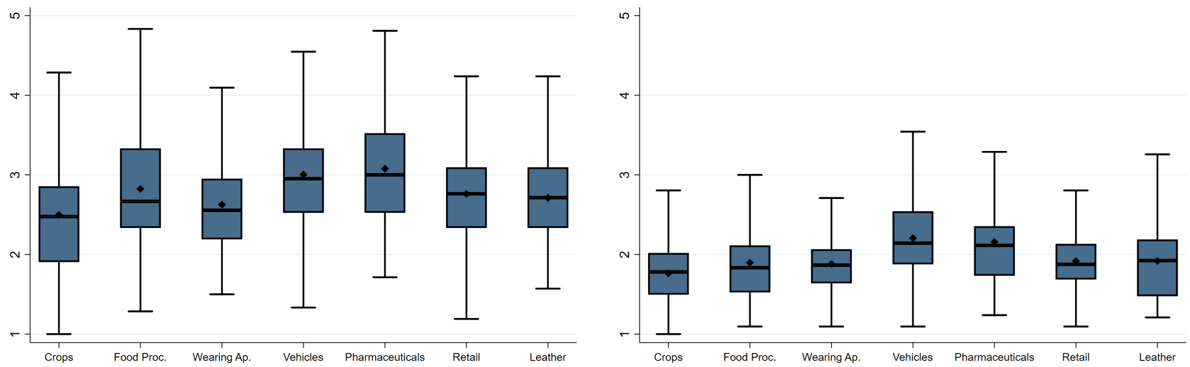
	ABF			GBF			SSBF		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Intensive margin	2.02	1.86	1.92	1.79	1.89	1.93	2.32	1.64	1.89
Extensive margin	2.71	2.73	2.69	2.52	2.73	2.76	2.92	2.73	2.43

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Technology measures are weighted by the sampling weights.

At the intensive margin, the sophistication of General Business Technologies is very low in Vietnam irrespective of the sector. Focusing on those sectors where the sample was stratified, Figure 10 shows box plots of the technology index figures for each sector and for both extensive and intense margins. Although average indices are very similar across sectors, Pharmaceutical companies have the larger index for the extensive margin, closely followed by Motor Vehicles. Meanwhile, variance across companies is very low in the Livestock sector and considerably large for Food Processing, Motor Vehicles, and Retail. In the intensive margin, there is little variance across sectors, with Motor Vehicles and Pharmaceuticals showing a slightly larger index. Also, by comparing Panels A and B in Figure 10 its clear that the gap between extensive and intensive margin holds even when controlling by sector. Within sectors the variance in technology use is also lower in the intensive margin and larger for livestock and leather at the intensive margin.

Figure 11 shows the predicted index values of the GBF index for the intensive and extensive margin measures and controlling for firm characteristics. As mentioned above, sector differences are marginal and larger at the extensive margin, with an average below 2 for the intensive margin. The results are similar for the predicted values by firm size. Although increasing in size, differences across firm size are small. Vietnam shows less heterogeneity

Figure 10: Sector GBF Index by Sector



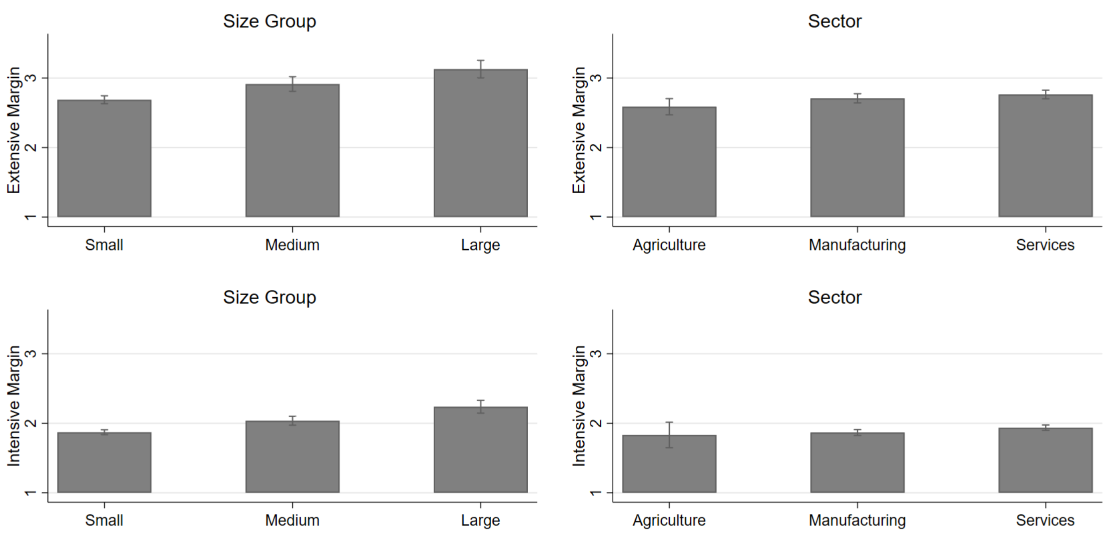
(a) Extensive margin

(b) Intensive margin

Note: Box plot of general business function index by sector.

across sectors and firm size than in other countries with data collected - Senegal and Ceará (Brazil).

Figure 11: General Business Functions in Vietnam - Heterogeneity



Note: Figure shows the predicted values of GBFs index by size and sector with confidence intervals from the Probit regressions controlling for other baseline characteristics. All estimates are weighted by sampling and country weights.

5 Sector-Specific Business Functions

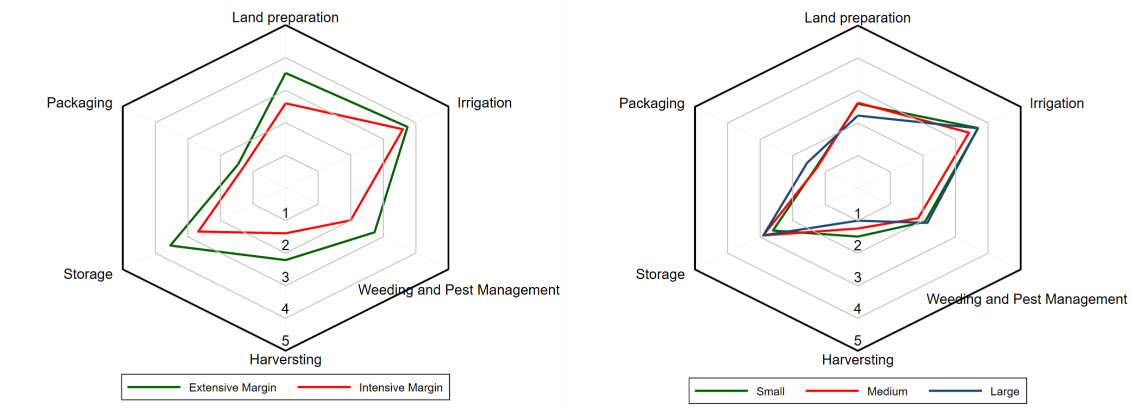
Sector specific business functions reflect the level of technologies that are specifically related to core production processes or service provisions. Overall, we observe significant heterogeneity in the level of technology used across business functions within firms in different sectors.

5.1 Agriculture

5.1.1 Crops

Technology use in crops uses low sophistication technologies and with large differences across functions. Vietnam is known for some agricultural exports like coffee beans, rice, cotton, peanuts, sugarcane and tea. Despite the importance of some of these cash crops, production remains mostly based on manual process, with slightly more advanced technologies for irrigation and storage. For tasks related to packaging, harvesting, and weeding and pest management, the intensive margin is smaller than 2.

Figure 12: Agriculture - SSBF



(a) Extensive and intensive SSBF (b) Intensive SSBF by size group

Note: Each line represents the index average across firms for each business function.

For the intensive margin, about 66% of farms in Vietnam still rely on manual harvesting, with only 10.8% using mechanized processes with machines or tractors. Similarly, the most used technologies for packing are human-operated machines (48%) and manual packing (40%). More advanced technologies are used in irrigation and storage. The most used type of storage facilities are facilities with cold or dry controlled environment (74%). In the case of irrigation, 44% of farms use small pumps, while 40% use drip or localized irrigation. Panel B in Figure 12 shows the intensive margin index for different size groups. The relationship between size and technology adoption varies accordingly with each function. For instance, larger firms use more advanced irrigation and packing technologies. However, this pattern is not repeated for land preparation and harvesting.

5.2 Manufacturing

5.2.1 Food Processing

For Food Processing, the majority of firms still rely on manual packaging and manual mixing and blending, as well as basic anti-bacterial and input testing methods. In the intensive margin, mix, blend and cook is the business function with the highest index, for which a significant share of firms is adopting manually operated machines. Yet, there is a significant gap to the frontier, with about 25% are still relying on manual process and an intensive margin index of 2.5. Although 47% of the establishments rely on the review of supplier testing, an equally large share (46%) use "human sensory" methods, which is the most basic procedure available to perform this task. For packaging, most firms (74%) use human operated machines as the more often used technologies; while for storage, about 44% relies on the most basic technologies (minimal protection or closed building).

Larger firms adopt more advanced methods for packing. Yet, the index is low and close to small and medium size firm indices. Panel B of Figure 13 shows the intensive SSBF by size group. Overall, except for anti-bacterial methods, large firms use slightly more advanced methods. Yet, the difference is small in comparison with small and medium firms and the gap to the frontier is significantly large.

Figure 13: Food Processing - SSBF

(a) Extensive and intensive SSBF (b) Intensive SSBF by size group

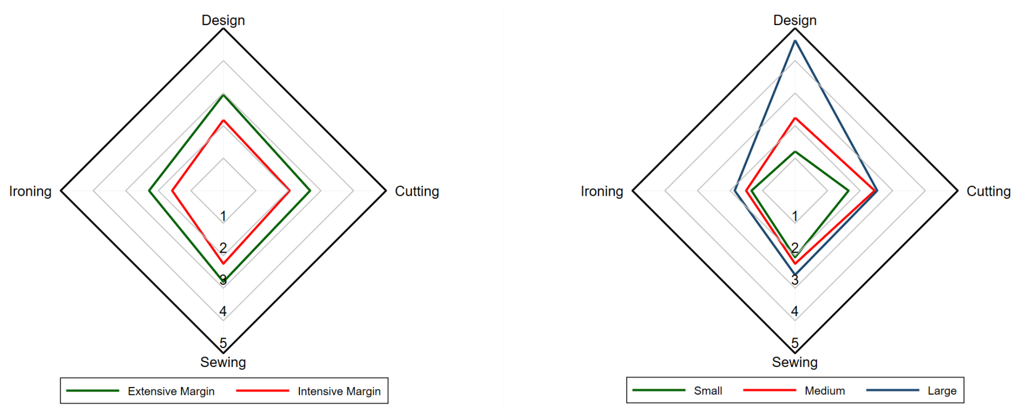
Note: Each line represents the index average across firms for each business function.

5.2.2 Wearing Apparel

Wearing and apparel has been a critical sector in the development of Vietnam, given its link to GVCs. Vietnam is one of the largest exporters for textiles, garments and clothing worldwide. Textile and clothing responds for about 16% of value added in manufacturing. Despite its relative importance, Figure 14 shows that most establishments sill use very basic technologies. The majority of firms make use of manual design and manual cutting, machine manually operated for joining parts, and manual ironing as the most used technologies. In the intensive margin, 46% of establishments use manual design and hand drawing; 22% use CAD or 3D design. For cutting, 63% use either manual cutting or manually operated cutting machines. Sewing is the business function with the highest index, yet very low, for which a large share of firms is adopting "machine manually operated" (about 62%) or "semi-auto sewing machine" (about 20%). On the other hand, ironing is the business function with the lowest index for the intensive margin, with 97% of establishments using one of the most basic methods; manual ironing (about 43%) or electric high-pressure steam iron (54%).

In design, most large firms are at the frontier. Yet, there is a significant gap in the other business functions. There is a positive association between firm's size and the intensive margin index across business functions. The association is larger for design, for which almost 80% of firms are using CAD or 3D design. On the other hand, for cutting, ironing and sewing, the difference among groups is small, as shown in Panel B.

Figure 14: Wearing Apparel - SSBF



(a) Extensive and intensive SSBF (b) Intensive SSBF by size group

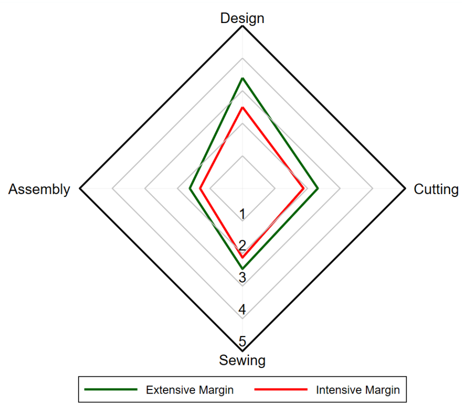
Note: Each line represents the index average across firms for each business function.

5.2.3 Leather and footwear

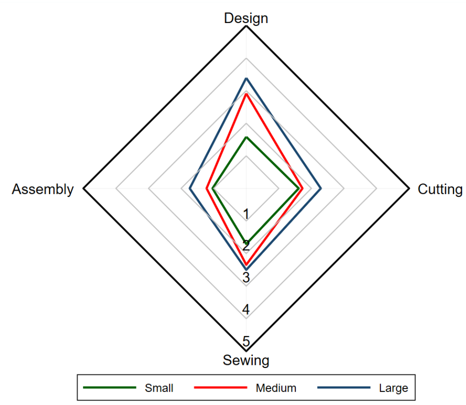
Leather and footwear is another relevant light industry in Vietnam, with the country being the third largest exporter of leather shoes in the world. Similarly to wearing apparel, most establishments in leather and footwear use very basic and manual methods for their business functions. Figure 15 shows that both extensive and intensive index are very low in the country, varying from 1.3 for assembly to 2.5 for design, in the intensive margin. In the intensive margin, 40% of establishments rely on manual design and hand drawing for drawing processes, while 33% use specialized 2D drawing software. For cutting, about 75% use either manual cutting or manually operated machines; sewing is also done mostly using manually operated machines (21%) and semi-operated machines (50%). Assembly is the lowest index, for which 70% of establishments use manual one station-based or conveyor based finishing methods.

Although large firms use more advanced design methods, other business functions are very low and close to those for small and medium size firms. In the intensive margin, large firms use slightly more advanced methods for cutting, sewing, and assembly; yet, panel B in Figure 15 shows that the gap to the frontier is significantly large even for large firms. Design is one exception, for which large firms are mostly using the most advanced techniques.

Figure 15: Leather and footwear - SSBF



(a) Extensive and intensive SSBF



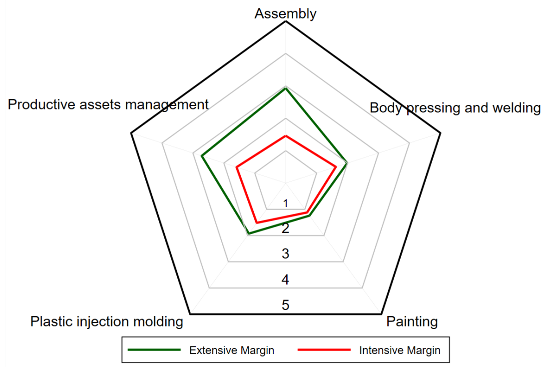
(b) Intensive SSBF by size group

Note: Each line represents the index average across firms for each business function.

5.2.4 Motor Vehicles

In the case of Motor Vehicles, the intensive margin indices are significantly low, ranging from 1.4 for assembly to close to 2 for plastic injection. Figure 16 suggests that on average establishments in the sector use basic technologies. In the case of body pressing, 21% of firms relies on welding of main body using operators. Also, 31% use "solvent-based painting using operators". On the other hand, there is a large gap between the extensive and intensive margin for assembly and productive assets management, suggesting that basic methods are also the most used ones. 57% still make use of "molding of non-visible interior plastic", while the more often used method for assembly is "machines fully controlled by operators" (60%).

Figure 16: Motor Vehicles - SSBF



5.2.5 Pharmaceuticals

In pharmaceuticals, an important share of establishments is using the most advanced method for their business functions; yet, variance is large across establishments. Extensive index varies from 3.2 for mixing and compounding to 3.7 in packaging, while intensive margin index shows a decline and varies from 2.3 for mixing and compounding to 3.5 for weighing and dispensing. The small gap between the extensive and intensive margin for weighing and dispensing suggests that this is a business function for which firms are intensively using the most advanced technology they use. In the intensive margin, about 60% of establishments use either HEPA or ultra HEPA air filtration; 75% use electronic scales for weighting, while 12% use automated systems, the most advanced method. Although 15% of companies still rely on manual mixing, about 74% use planetary mixers (43%) or high speed/shear granulators (34%); quality control is mostly done through electronic chromatography (49%) and packaging is mostly carried in automated packaging lines (53%).

Variance in pharmaceuticals is largely explained by size group differences. Panel B in Figure 17 shows intensive margin index according to size groups, suggesting a clear and positive relationship. Large firms use more advanced methods for all business functions. The gap between large and small firms is larger for packaging and quality control, while firms use very similar methods for weighing and dispensing.

Figure 17: Pharmaceuticals - SSBF

(a) Extensive and intensive SSBF

(b) Intensive SSBF by size group

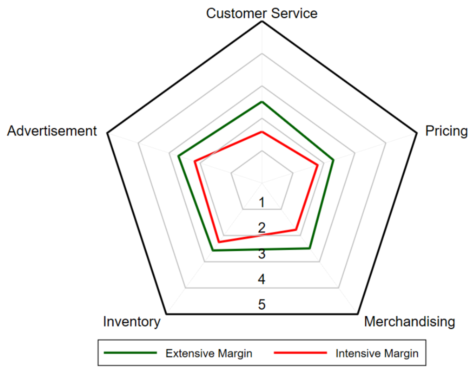
Note: Each line represents the index average across firms for each business function.

5.3 Services

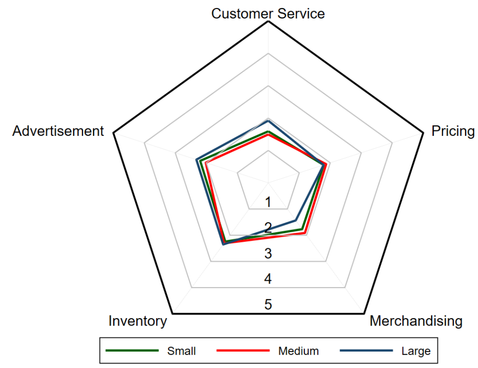
5.3.1 Retail and wholesale

In retail, the extensive margin index is close to 2.5 for all business functions, suggesting the use of basic methods across functions. In the intensive margin, almost 90% of firms provide the services at the premise (48%) or by phone (40%). In other business functions, such as pricing strategies, 24% uses "manual cost" and 67% use automated markup as the most frequently used technologies; about 44% relies on manual selection as the most used technology for merchandising, while 42% use category management tools; both being the most basic methods in this business function. Inventory is the business function with the highest intensive margin index, for which 66% of establishments use computer databases with manual updates as the most frequently used technology. Lastly, for advertisement, only 5% of companies are using either big data and artificial intelligence or search engine marketing; most of them rely on email or mobile phone (about 42%) and social media (about 30%). Overall, differences among size groups is very small; yet, except for merchandising, large firms use more advanced technologies in the intensive margin.

Figure 18: Retail and wholesale - SSBF



(a) Extensive and intensive SSBF



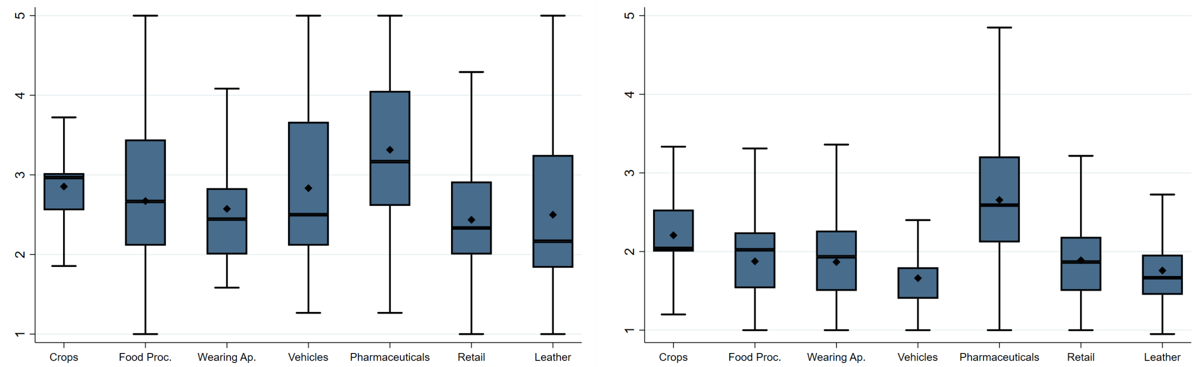
(b) Intensive SSBF by size group

Note: Each line represents the index average across firms for each business function.

5.4 Cross-sector differences in sector-specific technologies

Although sector specific functions are not comparable, Figure 19 helps us compare the variance within sectors and derive some important facts about the Vietnamese economy. First, the heterogeneity in SSBFs is much larger than for GBFs; the use of production technologies is more heterogeneous than the use of technologies for GBFs. Second, on average Pharmaceutical companies are using the most advanced sector specific technologies, both for the extensive and intensive margins. In the extensive margin, the variance in the Crops sector is the smaller, indicating very similar technologies across companies. Third, the figure also suggests that Food Processing, Motor Vehicles, and Wholesale and Retail show the larger variances. In the intensive margin, it is worth noting the large variance in the Pharmaceutical sector. An important share of establishments that are close to the frontier coexist with an equally important share of firms using very basic technologies at the intensive margin. On average, establishments in the Pharmaceuticals sector use more advanced sector specific technologies; while retail show the lower index.

Figure 19: SSBF - Sector Comparison



(a) Extensive SSBF

(b) Intensive SSBF

Note: Box plot of sector specific business function index by sector.

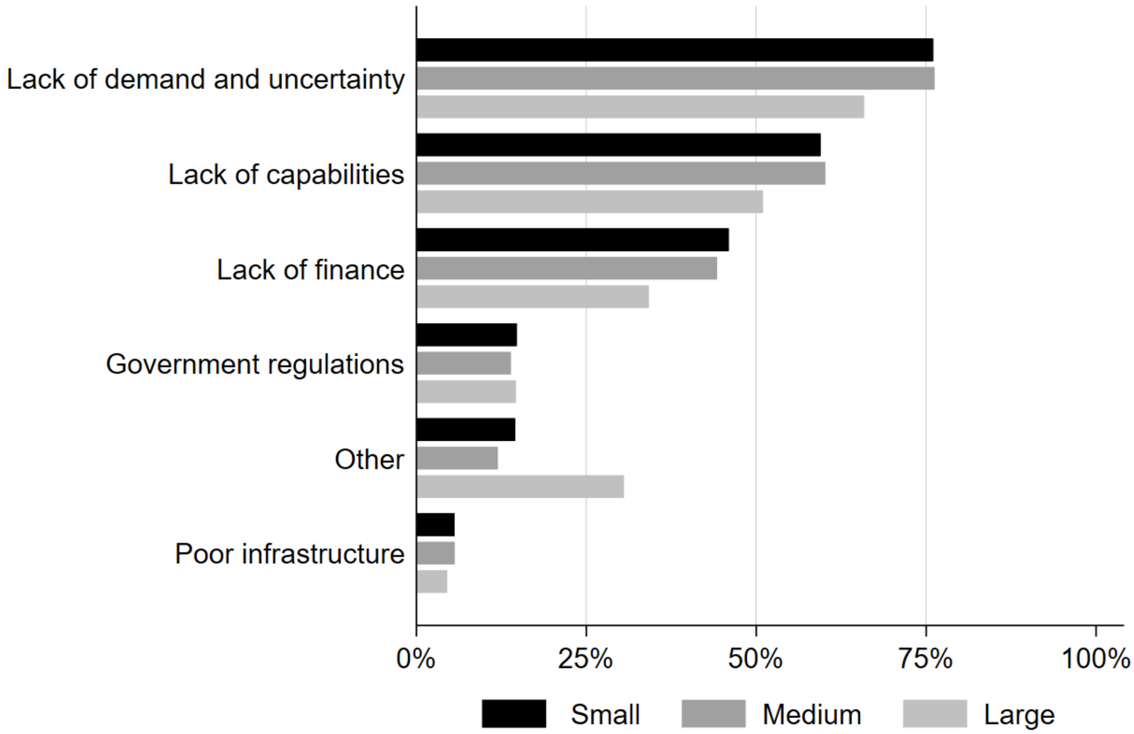
6 Barriers to Technology Adoption

Given the significant distance to the technological frontier for the average firm in Vietnam, a critical question for policy is what are the main barriers that constrain the adoption of more sophisticated technologies among firms. The survey provides some detailed information to try to shed some light on this question. We start with showing some of the key barriers identified by firms' managers and then analyze some factual barriers to adoption and use.

6.1 Perceived barriers to adoption

The survey asks managers to identify the three most important obstacles to the adoption and use of technologies. We group these obstacles in terms of lack of capabilities, finance, lack of demand or uncertainty, costly government regulations or poor technology enabling infrastructure (electricity, internet,...). Figure 20 describes the share of firms reporting main obstacles by size group. About 75% of small and medium companies see the lack of demand and uncertainty as a relevant barrier to adoption, followed by lack of capabilities and lack of finance. Lack of demand and uncertainty refer to uncertainty about the returns to invest in technologies and whether their demand justifies such investments. Lack of capabilities refer to lack of information on what technologies are available and also lack of skills to use the technology. Overall there is little variance across small and medium size firms, suggesting that these firms are facing the same types of obstacles irrespective of size. Almost 50% of small firms see lack of finance also as an important obstacle to use and adopt technology. Unreliable energy or internet (poor infrastructure) is the least important obstacle for adopting more sophisticated technologies, although the power outages outlined above could harm firms' decision to adopt as well.

Figure 20: Perceived Obstacles for Adopting Technology by Firm's Size



Note: Each line represents the index average across firms for each business function.

We estimate a linear regression model to analyze more formally the statistical correlation between the level of technology use and perceived obstacles, while controlling for the size of the firms, sector, and region (see Table 7). Most coefficients are not significant, and only financial constraints are associated with limited technology use for General Business Functions (intensive margin) and Sector Specific Business Functions (both in and extensive margin) in Vietnam. Perceived obstacles have been shown in the literature as poor predictors of actual variables. As a result, in what follows we investigate some of the actual information collected in the survey and their association to use and adoption of technologies.

Table 7: Perceived Obstacles for Adopting Technology and Technology Use

VARIABLES	GBF Ext	GBF Int	SBF Ext	SBF Int
Lack of capabilities	0.032	0.001	0.070	0.023
	(0.020)	(0.017)	(0.046)	(0.038)
Government regulations	0.040	0.023	0.067	0.047
	(0.028)	(0.027)	(0.052)	(0.057)
Lack of finance	-0.023	-0.039**	-0.140***	-0.073*
	(0.019)	(0.017)	(0.050)	(0.040)
Lack of demand and uncertainty	0.013	-0.039*	0.008	-0.011
	(0.024)	(0.022)	(0.052)	(0.048)
Poor infrastructure	-0.017	-0.014	-0.082	-0.124*
	(0.040)	(0.040)	(0.068)	(0.073)
Other	0.000	-0.001	0.061	0.026
	(0.034)	(0.027)	(0.073)	(0.060)
Ln (Employment 2018)	0.044***	0.051***	0.056***	0.041***
	(0.007)	(0.007)	(0.018)	(0.015)
Constant	0.805***	0.525***	0.952***	0.709***
	(0.063)	(0.045)	(0.105)	(0.086)
Observations	1,498	1,498	925	925
R-squared	0.120	0.131	0.151	0.115
Sector FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES

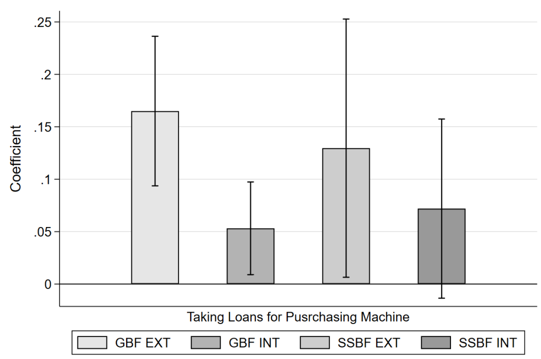
Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6.2 Financial Constraints

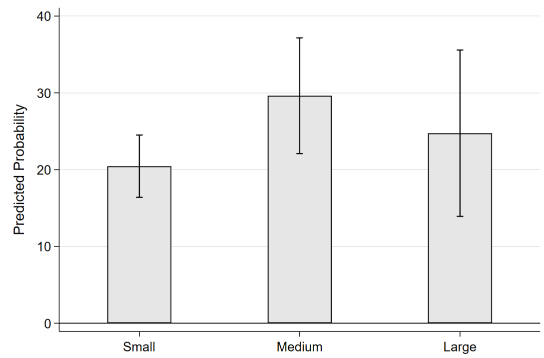
The result on the correlation of financial constraints and technology adoption above is nothing new, a large literature has analyzed this relationship. For instance, by studying a model of establishment dynamics with a producer-level data, Midrigan and Xu (2014) found that financial friction distort firm entry and technology adoption decisions, which results in lower level of aggregate productivity. Cole et al. (2016) provide a dynamic state model to explain that the efficiency of financial system with available technologies determines which technologies are adopted by firms across countries. Similarly, other studies also found suggestive evidence that the improvement of local financial systems affect firm-level technology adoption in the Russian Federation (Bircan and De Haas, 2019) and in agriculture in Ethiopia (Abate et al., 2016). Figure 21 panels (a) and (c) present the predictions of our measures of actual financial access - whether firms took loans and what interest rate - on the index of technology. Having a loan is positively correlated with the adoption index for GBFs, while for SBFs the correlation is not statistically different from zero. On the other hand, when looking at the correlation of the actual interest rates that firm face and technology sophistication none of the coefficients are statistically different from zero.

It is possible that most of the firms that state lack of finance as an important deterrent to technology adoption are the ones without any access to finance and therefore are excluded from panel (c). Figure 21 panels (b) and (d) describe the predicted values of having a loan and interest rate they face by firm size and sector, and controlling for other observable characteristics. Small firms have about 20% probability of having a loan, compared to medium firms that have almost 30% and large firms that have about 25% probability. Financial access is relatively low, especially when we consider large firms. By sector, and controlling for other factors, wearing apparel and other manufacturing firms appear to face larger interest rates on their loans.

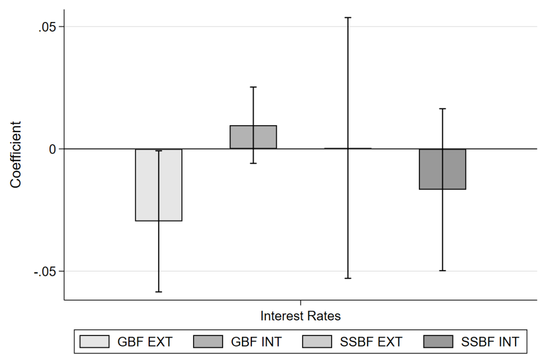
Figure 21: Access to Finance and Technology Use



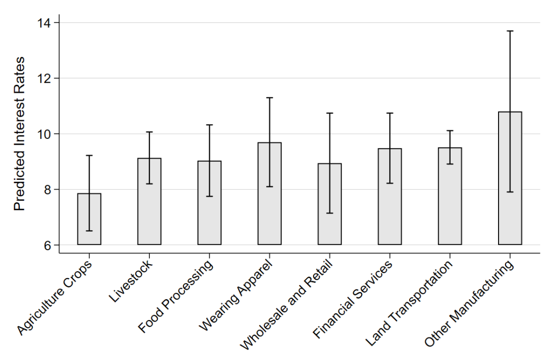
(a) Having loans and technology use



(b) Probability of having a loan by size



(c) Interest rate and technology use



(d) Interest rate by sectors

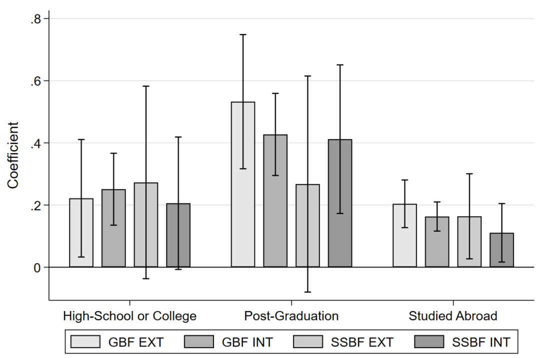
Note: Panel (a) and (c) provide the coefficients and 95% confidence intervals from regressions. Each technology measure is regressed on a dummy for taking loans to purchase machine/software and interest rates, respectively, while controlling for formality, sector, size, and regions. Panel (b) show the predicted probability of getting loans by size groups and confidence intervals from the Probit regression with controlling for other baseline characteristics. Panel (d) presents the predicted interest rates by sectors from the linear regression with controlling for other baseline characteristics. All estimates are weighted by sampling and country weights.

6.3 Firm capabilities

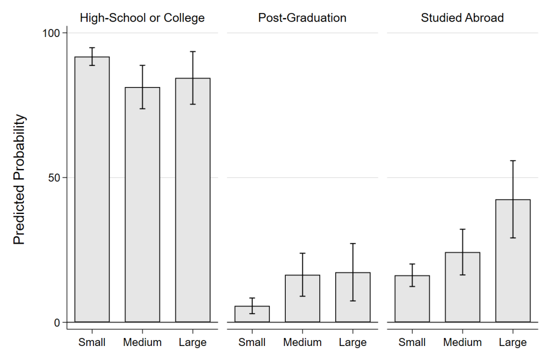
6.3.1 Management quality and skills

Lack of firm capabilities is the second most perceived obstacle as a barrier to adopt and use technology. Previous studies provide suggestive evidence that human capital is an important factor to adopt advanced technologies that require workers to have more advanced knowledge (Caselli and Coleman, 2001; Riddell and Song, 2017; Comin and Hobijn, 2004). In what follows, we explore the role of skills and managerial quality in technology adoption and use.

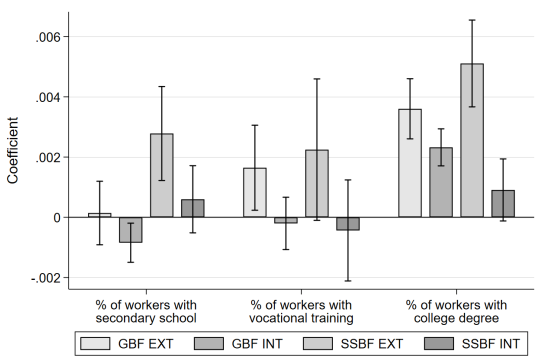
Figure 22: Skills of Managers and Workforce and Technology Use



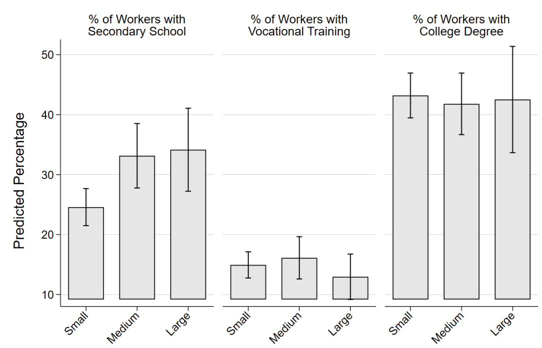
(a) Technology use and managers education



(b) Top managers human capital by size



(c) Technology use and workers skills



(d) Workers skills by size

Note: Panel (a) and (c) provide the coefficients and 95% confidence intervals from regressions. Each technology measure is regressed on a dummy for top managers' education (e.g, post-graduation and study abroad) and the percent of workers with different education levels (e.g., secondary school, vocational training, and college degree), respectively, while controlling for formality, sector, size, and regions. Panel (b) show the predicted probability of having top managers with BA+ or studying abroad by formality and size with confidence intervals from the Probit regressions controlling for other baseline characteristics. Panel (d) presents the predicted percent of workers with different education by formality and size from the linear regressions controlling for other baseline characteristics. All estimates are weighted by sampling and country weights.

Figure 22 panels (b) and (d) describe the prediction of top managers and workers education by firm size controlling for different firm characteristics such as sector, size and region. The results show that most managers have a high school, bachelor or college degree.[11] The probability is also very high for managers in small firms. There is a clear and significant relationship between firm's size and the probability of top managers studying abroad, with around 40% probability in large firms and one third of this in small firms. When it comes to workers skills, the share of workers with high school, bachelor or college degree is not related to firm's size, with similar predicted probabilities for all size groups.

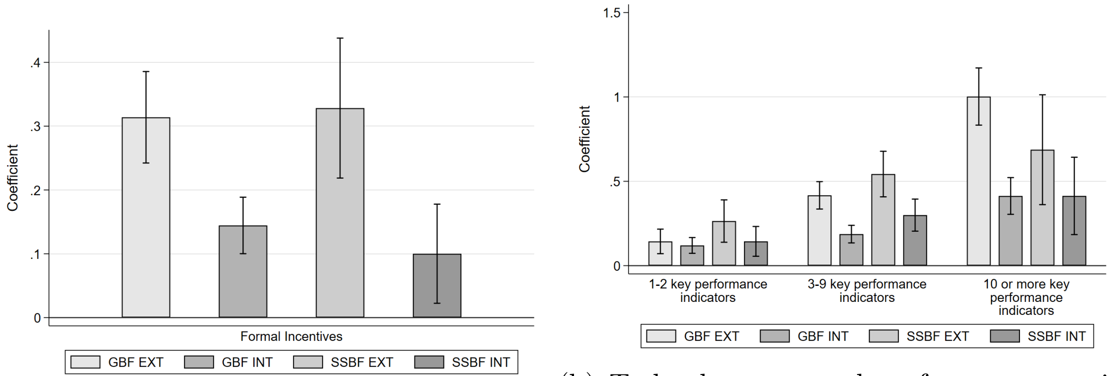
Panels (a) and (c) present the predictions of managers and workers education on the index of technology. In terms of managers education, the coefficient shows that having a manager that has a post-graduation increases the technology index between .2 and .55; similarly to having the manager have studied abroad - between .13 and .2. On the other hand, the results for the skills of the workforce are surprising. The effect of having a larger percentage of workers with secondary skill and vocational training does not have any predicted effect on the sophistication of the technology index; and having 1% more workers with a college degree does not increase the technology index very much. Thus, the education of managers is more highly correlated to technology sophistication than the skills of workers.

We explore the issue of managerial quality and the impact on the technology index more in detail using some of the questions of the World Management Survey (WMS) (Bloom and van Reenen, 2007, 2010). The questionnaire asks if the firm makes use of formal incentives and the number of performance indicators it uses. We use these two measures and compute their predictions on the index of technology.

Figure 23 shows that firms using formal incentives for workers (panel a) have a higher index for both extensive and intensive margin; ranging from 0.1 at the intensive margin to a larger 0.3 for both extensive margin figures. More importantly, Panel (b) shows that firms with more performance monitoring indicators are using more advanced technologies, and the coefficient is large. Using more than 10 performance indicators is associated with having between .4 and 1 units of higher technology index. Thus, management quality proxied by the use of formal incentives and, especially, performance monitoring is positively associated with the use of more sophisticated technology.

[11] In Vietnam university and "college" degree are different; and the latter is an easier and less rigorous type of tertiary education compared to university.

Figure 23: Management Quality and Technology Use



(a) Technology use and formal incentives

(b) Technology use and performance monitoring

Note: Panel (a) and (b) provide the coefficients and 95% confidence intervals from regressions. Each technology measure is regressed on a dummy for providing formal incentives and performance indicators, respectively, while controlling for formality, sector, size, and regions. All estimates are weighted by sampling and country weights.

6.3.2 Awareness, information and overconfidence

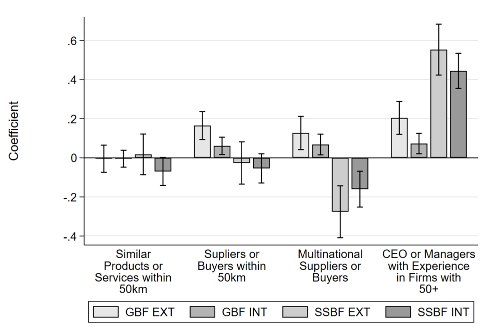
Flows of information from links with MNEs and other firms can facilitate technology adoption by providing know-how and incentives. There is some evidence that these information spillovers are more likely to occur when firms are geographically closer to other large firms producing similar products or providing similar services (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010), and do business with those firms as well as with other multinational firms (Alipranti et al., 2015). This is especially important in a country like Vietnam with a larger MNE presence and also important policy instruments such as tax incentives aiming at facilitating spillovers from MNEs.

Figure 24 (panel b) shows the likelihood of having similar firms and links to MNEs. A high share of large firms have similar products or services within 50 km (72%) and supplier or buyers within 50 km (70%), and business relationship with multinational companies (36%). The likelihood for smaller firms is much lower, around 60%, although still high. On the other hand, when we look at links to MNEs, either through a supply chain or through managers experience, the likelihood for smaller firms to have such linkages is very small, around 10%-17%. This likelihood increases substantially for larger firms that have 30% likelihood to have value chain relationship with MNEs and 46% probability of having managers with MNEs. [12] Thus, if information spillovers exist, smaller firms are unlikely to benefits because do not possess sufficient links.

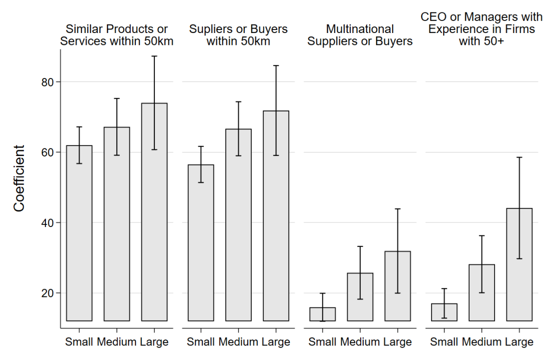
[12] In terms of sector, the share is of 7% for agriculture, 17% for manufacturing, and 21% for services.

Figure 24 (panel a) explores how these linkages are correlated with technology use. Interestingly proximity in terms of product and value chain is not statistically significantly correlated with the sophistication of the technology index. In the case of linkages with GVCs we find a positive and statistically significant correlation for the GBF index, but a puzzling negative an statistically significant correlation with the SSBF index. Looking at the intensive margin measures, these linkages are associated with a 0.05 higher index and 0.1 lower SSBF index. The coefficients for having a manager or CEO with MNE experience are, however, all positive and statistically significant, ranging from 0.05 for GBF intensive margin to 0.4 for SSBF intensive margin. Information flows and spillovers seem to occur primarily through managers and CEOs experience.

Figure 24: Information Spillovers and Technology Use



(a) Technology use and information spillovers

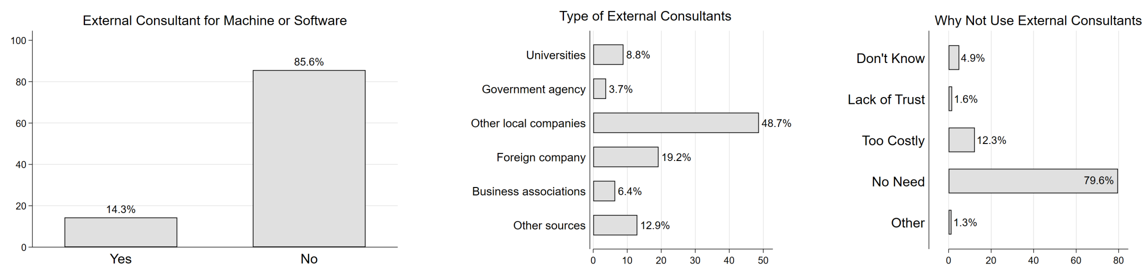


(b) Information spillovers by firm size

Note: Panel (a) provides the coefficients and 95% confidence intervals from regressions. Each technology measure is regressed on a dummy for providing formal incentives and performance indicators, respectively, while controlling for formality, sector, size, and regions. Panel (b) shows the predicted probability of each awareness variable on formality from the Probit regressions with controlling for other baseline characteristics. All estimates are weighted by sampling and country weights.

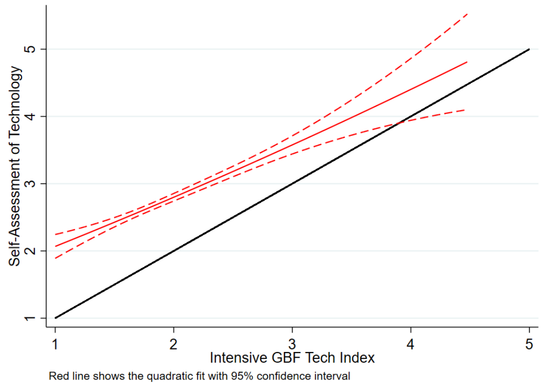
Another potential source of knowledge for technology is the use of external consultants. Shin (2006) found that getting external consultant plays an important role in adopting IT technologies by small businesses, particularly when CEOs or managers do not have technical expertise. Comin et al. (2016) also show that a company may seek advice from public organizations with prior experience in the technology. The survey asks for those companies that have purchased any new equipment and software in the last two years about the sources of information used for the purchase and installation. In Vietnam, very few establishments have used external consultants as a source of information. Only 14% of firms have used external consultants for this purpose, of which 48% relying on other local companies (see Figure 25) and 19% on foreign companies. Business associations and universities were used only by 6.5% and 8.9% of firms respectively. Among those firms that have not used external consultants, the most common reason reported for do not access external consultants is "no need" with about 80% of firms and 12.3% suggested it was too costly. This suggests significant unwillingness to use consultants, either due to unawareness from firms or also due to lack of quality of some of the consultants available.

Figure 25: Sources of Information for Machinery and Software

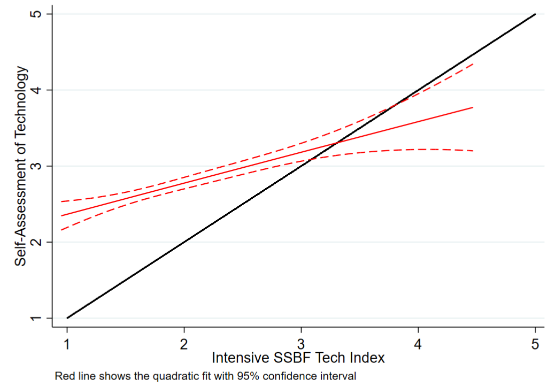


We further investigate the lack of confidence in the use some external sources of information. One reason for not adopting new technologies is overconfidence in the level of adoption they have. If firms think that their level of technology is higher than what it actually is, it is difficult that they are willing to adopt and use new technologies. The question then becomes to what extent firms are aware of their technology gap. The survey, prior to the technology questions to prevent any bias in the self-assessment, asks each manager to provide a self-assessment of the sophistication of their technology from 1 to 10 (here re-scaled to 1 to 5). Clearly, when the self-perception is much larger than the actual index (pairs placed above the 45 degrees line), managers are too confident on their technology level and it is unlikely that they will be keen on upgrading. Figure 26 maps their self-assessment of their technological level with the actual measurement index in the survey. Panels (a) and (b) shows firms' self-assessment with respect to other local firms, while panels (c) and (d) vis-a-vis with global firms in their sector. When compared with other firms in the country, firms show a large degree of overconfidence, in the sense that they think they are better than they are. The opposite occurs when comparing with global firms. This suggests that while overconfidence is not very high, for firms that compete primarily in the domestic market, the willingness to upgrade technologies is very low; for both GBFs and SSBFs. On the other hand, firms competing in international markets may have more incentives and willingness to upgrade their technologies since their perception is of a technology gap.

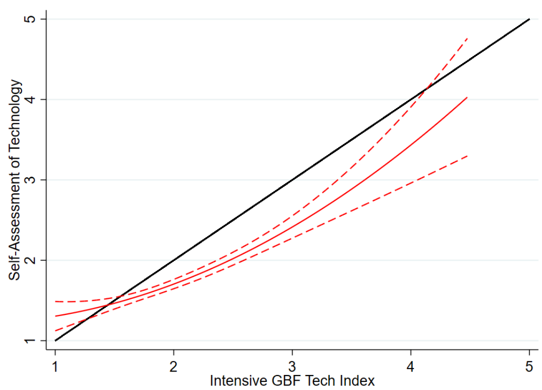
Figure 26: Association Between Self-Assessment and Technology Adoption



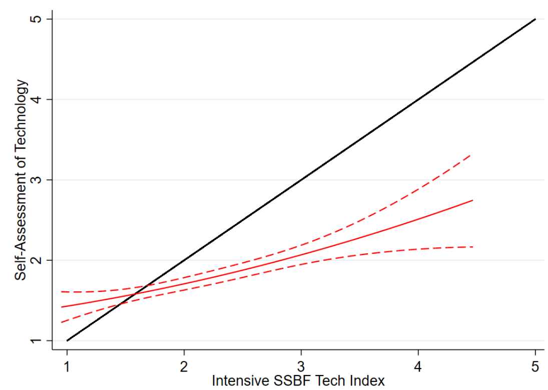
(a) In relation to other firms in the country



(b) In relation to other firms in the country



(c) In relation to the most advanced firms in the world



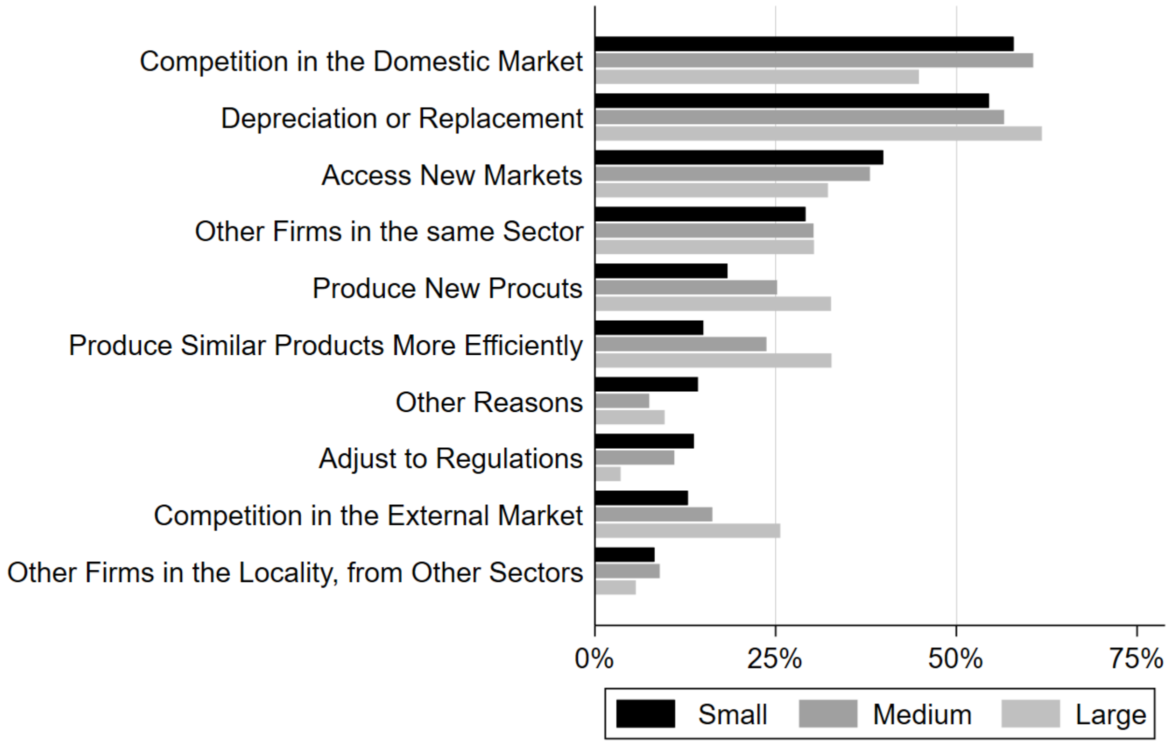
(d) In relation to the most advanced firms in the world

Note: Red line shows the quadratic fit with 95% confidence interval. Each technology measure is regressed on firms self-assessment with respect to other firms in the country (panels (a) and (b)) and the most advanced firms in the world (panels (c) and (d)), while controlling for sector, size, and regions.

6.4 Access to markets and competition

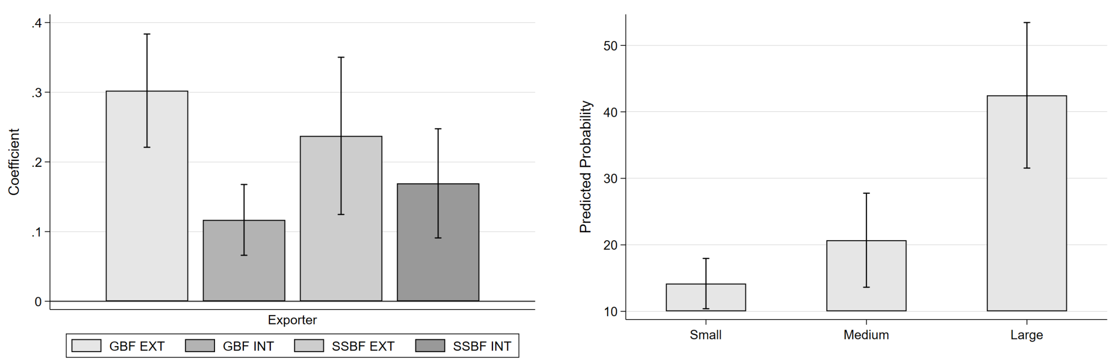
The survey also asks firms about their top three drivers to adopt technology. Figure 27 describes the share of firms reporting reasons to adopt by firm size group. Most firms adopt new technologies either due to depreciation or replacement or competition in the domestic market. This finding is consistent with the previous studies that competition may affect firm-level technologies (Milliou and Petrakis, 2011). Although the depreciation motivation is not so positive since it may imply a pure replacement of technology without upgrading. Firms also adopt new technologies aiming to access new markets and produce more efficiently. There is also some clear differences across size groups. For instance, competition in the external market is a more important reason for larger firms, while government regulations is a more common reason for small firms.

Figure 27: Main Reason to Adopt New Technologies



Note: Each bar represents the percentage of firms that selected this reason among the three main reasons to adopt.

Figure 28: Association Between Exporters/Importers and Technology Adoption



(a) Technology and exports

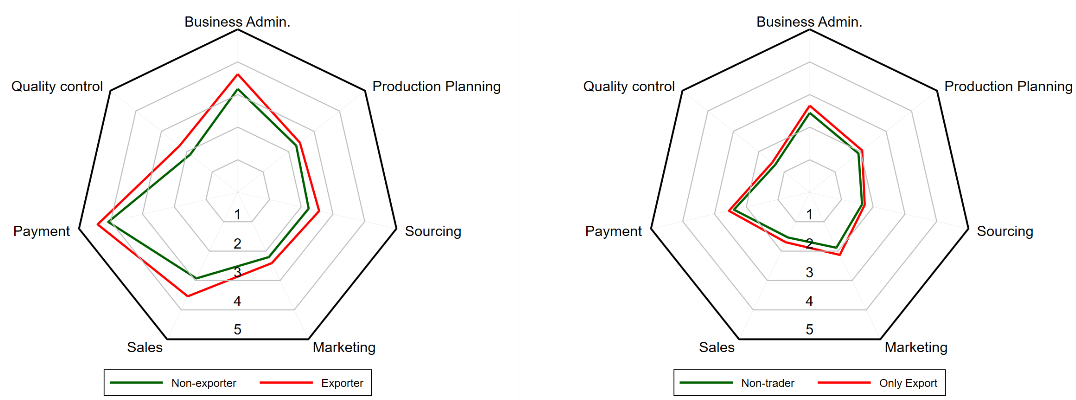
(b) Exporting status and size

Note: Panel (a) provides the coefficients and 95% confidence intervals from regressions. Each technology measure is regressed on exporter/importer dummies, respectively, while controlling for formality, sector, size, and regions. Panel (b) shows the predicted probability of exporter/importer status on size from the Probit regressions with controlling for other baseline characteristics. All estimates are weighted by sampling and country weights.

Access to international markets can have large effects to productivity via competition and learning, and these channels can also result in the use of more sophisticated technologies. There is a large literature that investigates if exporting firms become more productive after exporting, learning-by-exporting, or if more productive firms self-select into exporting (Haidar, 2012; Temouri et al., 2013; Yang and Mallick, 2010). Yet, even though there is an overall concordance that exporting firms are more productive, little is known about the extent that these differences are associated to technology and also the extent of causality from trade to technology adoption.

We estimate linear regressions to analyze the statistical association between the level of technology use and exporting. [13] Figure 28 panel (b) shows the estimated probability of exporting by firm size. As expected, there is a large correlation between size and exporting status, but the probabilities of participating in exporting are low for small (13%) and medium (20%), but higher than in other countries; reflecting the large export orientation of Vietnamese firms. Panel (a) shows the relationship between trade status and the technology index. Firms that export tend to have between .11-.3 use of more sophisticated technologies than non-exporters at the intensive margin. The technology premium associated to exporting is important. Figure 29 confirms these differences, although they are narrow when it comes to the intensive margin. Exporting companies use more advanced technologies for quality control, sourcing, business administration and production planning.

Figure 29: Technology Index by Business Function and Exporting Status



(a) Extensive margin (b) Intensive margin

Note: Each line represents the index average across firms for each business function.

Finally, we look into another channel of international activity that is foreign ownership. Figure 30 shows the GBF indices for domestic and foreign owned firms, defined as at least 50%

[13] In our sample, 17% of firms are exporters.

foreign capital.[14] Foreign firms use more sophisticated technologies, especially for quality control, business administration, production planning and payment methods.

Figure 30: Technology Index by Business Function and Ownership Status

(a) Extensive margin

(b) Intensive margin

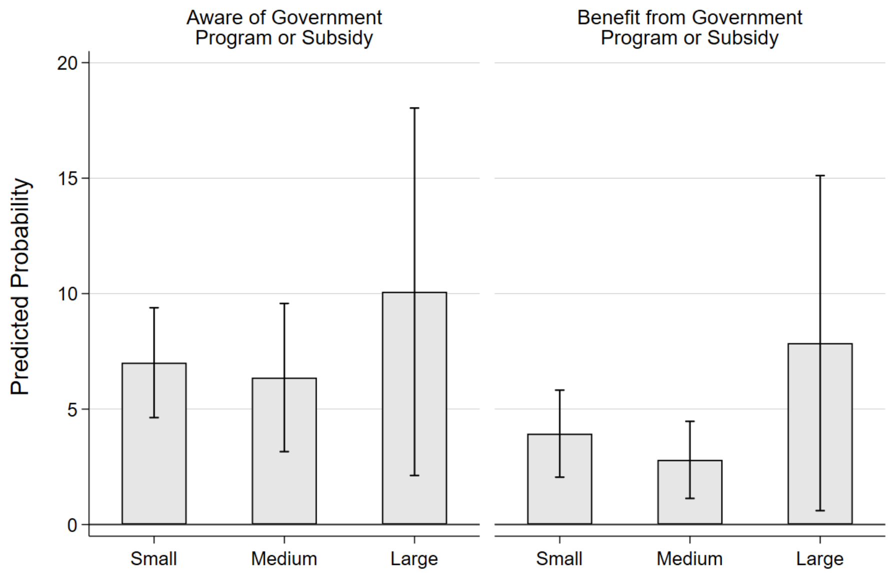
Note: Each line represents the index average across firms for each business function.

6.5 Access to government support

Public policies can try to address some of the barriers highlighted above to technology adoption, especially regarding lack of capabilities , information and skills. Vietnam has only a few policy instruments to support technology (World Bank, 2020), but only a few firms in Vietnam are aware of and benefit from government programs or subsidies to support technology adoption. Figure 31 shows the predicted probability of both awareness and the chance of benefiting of government program or subsidy for technology. Small and medium size firms are less likely to be aware of and benefit from government program or subsidy compared to large firms. Large firms benefit more from these programs, with a larger probability of benefiting (about 10%) than medium and small firms (3.7%). Similarly, large firms have a larger probability of benefiting from these programs. Yet, the share of companies aware of these programs is very small. World Bank (2020) describes in the context of innovation projects the large concentration of beneficiaries around Hanoi and the very low outreach of these programs. These results reinforce this finding and reflects in part the fact that there is not much support available, but more importantly it highlights the need for wider dissemination of existing support.

[14] Our sample includes 17.4% foreign firms.

Figure 31: Awareness of Government Program and Subsidy



Note: Figure shows the predicted probability of the awareness of government program or subsidy by size with confidence intervals from the Probit regressions controlling for other baseline characteristics. All estimates are weighted by sampling and country weights.

6.6 Summary on barriers and drivers

As a final exercise, we estimate linear regressions to analyze the statistical association between the level of technology adoption and some of the variables discussed in this section, while controlling for firm's size, sector, and region (see Table 8). Managers' previous experience is positively associated with technology use in the intensive margin for both general and sector specific business functions; managers' experience in large firms also has a positive impact on SBFs. There is also a positive association with the share of workers with a college degree and the use of eternal consultants; in the case of external consultants, the impact is larger for SBFs. Overall, however, it is hard to explain technology use, and only one-third of the total variance in technology is explained by these variables.

Table 8: Explaining technology Use

VARIABLES	**GBF Ext**	**GBF Int**	**SBF Ext**	**SBF Int**
Loan for Machine	0.017	0.013	0.029	0.037
	(0.021)	(0.018)	(0.047)	(0.047)
Similar Products in 50km	-0.019	-0.021	-0.035	-0.053
	(0.021)	(0.020)	(0.049)	(0.049)
Supplier and Buyers in 50km	0.054**	0.032	-0.015	-0.036
	(0.022)	(0.020)	(0.050)	(0.048)
Supplier or Buyer MNCs	0.041	0.037*	-0.080	-0.048
	(0.026)	(0.021)	(0.053)	(0.049)
Manager Experience in Large Firms	0.032	0.008	0.176**	0.191***
	(0.025)	(0.022)	(0.070)	(0.064)
Use of External Consultant	0.074**	0.032	0.155***	0.099*
	(0.031)	(0.025)	(0.058)	(0.059)
Benefit from Government Support	0.162***	0.044	0.007	-0.027
	(0.048)	(0.033)	(0.052)	(0.074)
Manager with University or More	0.031	0.041**	0.020	0.094***
	(0.024)	(0.019)	(0.039)	(0.034)
% of Worker with College	0.001***	0.002***	0.001*	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Log Total Employees 2018	0.035***	0.049***	0.045**	0.019
	(0.008)	(0.007)	(0.021)	(0.017)
Constant	0.735***	0.369***	0.859***	0.629***
	(0.049)	(0.038)	(0.079)	(0.070)
Observations	1,391	1,391	864	864
R-squared	0.355	0.372	0.364	0.300
Sector FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES

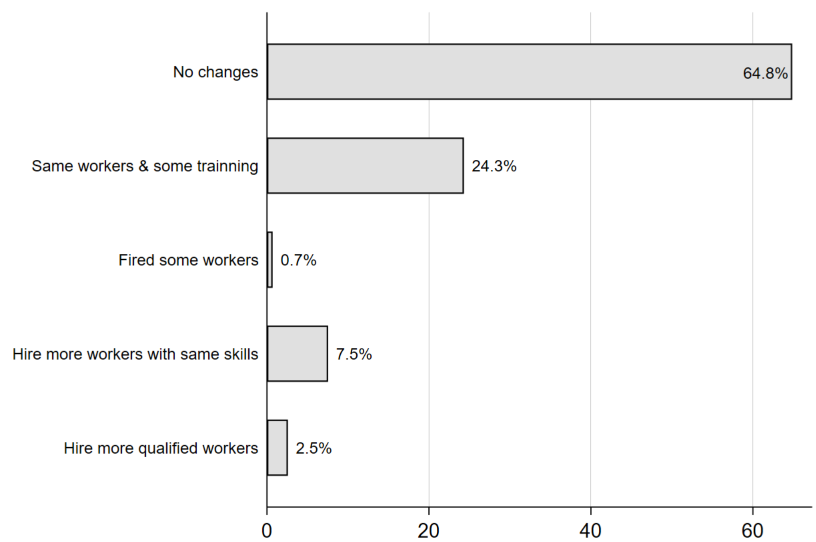
Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7 Technology and Employment

One of the most important topics in relation to technology in the last decade is the relationship between technology use and employment. The emergence of advanced labor-saving technologies has triggered a wealth of evidence in more advanced countries on job polarization (Autor et al., 2006; Acemoglu and Autor, 2011). In the survey, we have several questions related to employment to shed some light to employment effects.

The first set of questions relate to adjustment for firms that adopt new technologies. When asked about how firms adjust their labor to the acquisition of a new machine, equipment, or software, more than 79% of firms say that they do not change the number of workers. For almost two-thirds of the firms there is no adjustment on either employment or the level of skills, and about 24% suggest that they offer some training to current workers (Figure 32). Only in a very small number of firms, about 0.7%, there is a reduction in the number of workers as a mechanism of adjustment for the acquisition of new technologies. Even in 10% of firms they actually increase the number of workers with same skills than current workers possess (7.5%) or hire more workers with more qualified skills (2.5%). At first sight there is no evidence of labor savings associated to adopting new technologies.

Figure 32: How Firms Self-Report Their Adjustments to New Technologies?



We research the relationship between the technology index and employment more formally, and regress employment growth - between 2016 and 2018 - and our variable of technology adoption and use. Table 9 shows the estimates across different measures of technology and controlling for the initial size of the firm, their age, sector, region, foreign ownership, and exporting status. Although the coefficients are positive, the correlation between firm growth and the level of technology is not statistically significant, and we can explain only 30% of the variation in employment. Only for the intensive margin measures of GBFs we find some marginal statistical significance. Somehow surprising, we cannot find a statistically significant correlation between firm employment growth and technology sophistication, maybe as a result that we cannot observe changes in technology sophistication.

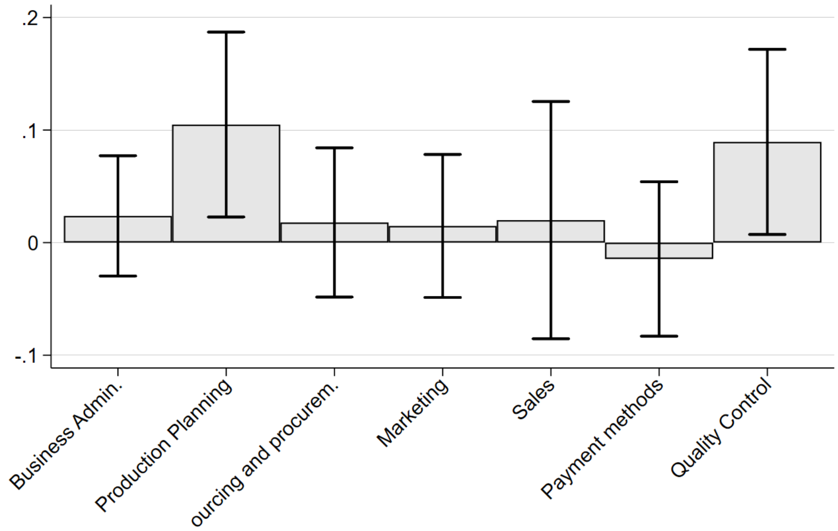
One potential explanation is also the fact that aggregate indices may aggregate important business functions for firm performance with others less important. Figure 33 estimates the same relationship for individual GBFs at the intensive margin and finds that except for production planning and quality control, the coefficients are not significantly different from zero.

Table 9: Employment Growth and Tech Adoption (Extensive and Intensive Margins)

	(1)	(2)	(3)	(4)	(5)	(6)
ABF Ext	0.026	0.044				
	(0.059)	(0.054)				
GBF Ext			0.026	0.052		
			(0.051)	(0.046)		
SBF Ext					0.024	0.040
					(0.048)	(0.043)
Ln (Employment 2016)	-0.233***	-0.267***	-0.251***	-0.266***	-0.233***	-0.266***
	(0.034)	(0.042)	(0.035)	(0.037)	(0.034)	(0.042)
Constant	0.524***	0.658***	0.612***	0.681***	0.535***	0.665***
	(0.168)	(0.240)	(0.155)	(0.196)	(0.136)	(0.218)
Observations	795	795	1,303	1,303	795	795
R-squared	0.189	0.302	0.195	0.271	0.189	0.303
Firm characteristics	NO	YES	NO	YES	NO	YES
Sector FE	NO	YES	NO	YES	NO	YES
Region FE	NO	YES	NO	YES	NO	YES
ABF Int	0.078	0.126				
	(0.104)	(0.096)				
GBF Int			0.121*	0.139*		
			(0.073)	(0.072)		
SBF Int					0.047	0.075
					(0.068)	(0.062)
Ln (Employment 2016)	-0.234***	-0.269***	-0.257***	-0.272***	-0.232***	-0.265***
	(0.035)	(0.043)	(0.036)	(0.038)	(0.034)	(0.042)
Constant	0.446**	0.536**	0.468***	0.575***	0.501***	0.617***
	(0.196)	(0.252)	(0.138)	(0.186)	(0.144)	(0.217)
Observations	795	795	1,303	1,303	795	795
R-squared	0.190	0.306	0.199	0.274	0.190	0.305
Sector FE	NO	YES	NO	YES	NO	YES
Region FE	NO	YES	NO	YES	NO	YES

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Firm characteristics include firm's age, trading status, and a dummy for foreign owned companies.

Figure 33: General Business Functions and Employment Growth



Note: The figure provides the coefficients and 95% confidence intervals from regressions. Job growth is regressed on each specific general business function at the intensive margin, while controlling for sector, size, and regions.

A final important element to explore is how adoption of more sophisticated technologies affects the skill composition towards skilled workers; the skill bias technological change hypothesis. To investigate this relationship, we analyze the correlation between the technology indices and changes in the skill composition of the firm based on existing occupations in 2016 and 2018. We use as a proxy for high-skill intensity the share of high-skilled (CEOs and managers, professionals, and technicians) on total workers, which also include low-skilled (clerks, production, and service workers) occupations. We then take the difference of this share between 2016 and 2018 and use it as a dependent variable.

Table 10 shows the results of the estimated coefficients controlling various firms characteristics including initial size of the firm. The correlations are not statistically significant across all indices. [15] We do not find clear evidence of skill biased technological change, or at least there is no clear association between technology use and changes in skills composition.

[15] This does not necessarily mean that these technologies are or are not unskilled-biased, given that the results could be driven by the growth effect. Yet, evidence in the literature suggests that technologies such as online platforms used for export sales can lead to reduction in the wage skill premium Cruz M (2020).

Table 10: Change in the Share of High-Skill Occupations and Tech Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
ABF Int	0.005	0.001				
	(0.019)	(0.018)				
GBF Int			-0.002	-0.002		
			(0.016)	(0.016)		
SBF Int					0.007	0.003
					(0.012)	(0.012)
Ln(Employment 2016)	0.043***	0.052***	0.045***	0.050***	0.043***	0.052***
	(0.008)	(0.010)	(0.006)	(0.006)	(0.008)	(0.010)
Constant	-0.119***	-0.154**	-0.119***	-0.151***	-0.123***	-0.158***
	(0.043)	(0.064)	(0.032)	(0.050)	(0.034)	(0.060)
Observations	795	795	1,303	1,303	795	795
R-squared	0.134	0.224	0.159	0.209	0.135	0.224
Firm characteristics	NO	YES	NO	YES	NO	YES
Sector FE	NO	YES	NO	YES	NO	YES
Region FE	NO	YES	NO	YES	NO	YES

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm characteristics include firm's age, trading status, and a dummy for foreign owned companies.

8 Conclusions

This paper provides a very granular view of technology adoption and use in Vietnam. We show that the average Vietnamese firm is far from the technological frontier and below the technology sophistication of firms in the north of Brazil. These technology gaps are on average similar across sectors, while the manufacturing sector faces the largest gap. Also, while there is almost universal access to the internet, few firms use their own website and sell online intensively, which suggests, given that the survey was implemented before the COVID-19 pandemic, lack of readiness for the digital adjustment required by the pandemic shock. Also, the use of Industry 4.0 technologies is very incipient in Vietnam. The results also point towards specific business functions where the technology gap is larger, such as quality control, production planning, sales or sourcing and procurement.

We also explore in detail some of the critical barriers to technology adoption and use. The results emphasize the importance of managerial human capital and quality as critical for technology use, more than workers' skills. In addition, even if there is a clear correlation between technology sophistication and labor productivity, overconfidence and the fact that firms are reluctant to rely on external sources of information, with also a total lack of co-operation with public institutions and universities, makes technology upgrading challenging. Unless these barriers to external links are broken.

As the large shock of the COVID-19 pandemic starts vanishing and governments focus on strengthening the recovery, it is critical to put technology upgrading at the center of the policy agenda. The imperative of digitalization at the peak of the lockdown restrictions and the lack of readiness of Vietnamese firms translated into reductions in revenue of 50% on average (see Vietnam BPS results). The risks of re-shoring with the implementation of Industry 4.0 threatens the very successful export oriented Vietnamese model. All these challenges demand a renewed focus on the technology upgrading of the Vietnamese economy. However, although the findings of this paper can aid the design of specific technology upgrading programs; (World Bank, 2020) shows that existing support policies for technology upgrading are still underdeveloped and are not reaching out enough to firms. This is confirmed by the lack of awareness of firms about support policies in our data. Developing these technology upgrading programs and expanding their coverage will be critical for Vietnam in strengthening the recovery and accelerating its convergence to a high-income country.

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Appendix

A The structure of the survey

Cirera et al. (2020) provide more details about the methodology and data collection of the survey. The FAT is organized in five modules:

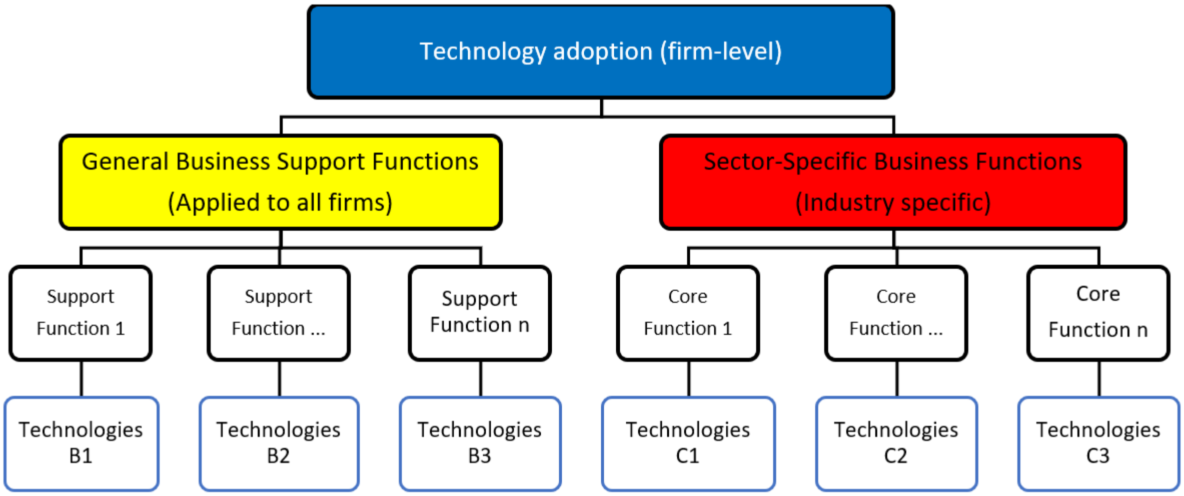
- Module A– Collects general information about the characteristics of the establishment.
- Module B – Covers the technologies used in eight generic business functions.
- Module C – Covers the use of technologies for functions that are specific to each of ten industry and services sectors
- Module D – Includes questions about the drivers and barriers for technology adoption.
- Module E – Collects information on employment, balance sheet and performance, which allow us to compute labor productivity and other measures at the company level.

Modules B and C collect the information to measure technology adoption, while the other modules collect information on firm characteristics, performance and variables that can provide information on the barriers and drivers of technology adoption.

The survey differentiates between general business functions that all firms conduct regardless of the sector where they operate (e.g. businesses administration related human resources and finance, production planning, sourcing and procurement, sales, method of payment) and sector specific functions/production processes that are relevant only for companies in a given sector (e.g., food refrigeration in food processing, or sewing in apparel). Information about technologies used in the former is collected in module B, while information on sector-specific technologies is collected in module C.

To design modules B and C, the survey draws upon the knowledge of experts in production and technology in various fields and sectors. These experts provided their knowledge on: i) what are the key general and sector-specific business functions, ii) what are the different technologies used to conduct the main tasks in each function, and iii) how are the different technologies related, both in terms of their sophistication and the degree of substitutability between them. These key businesses functions and technologies identified in modules B and C were validated by sector specialists.

Figure A1: Firm-Level Adoption of Technology (FAT) Conceptual Framework



B The technology index

A full description of the indices can be found in Cirera et al. (2020). Let's consider a function f with N_f possible technologies. Based on the experts' assessment we order the technologies in a function according to their sophistication, and assign them a rank $r_i \in 1, 2, ..., R_f$. Because several technologies may have the same sophistication, the highest rank in a function $R_f \leq N_f$.[16] Combining the technology rankings with the information collected by the FAT survey on the technologies used by a firm, we construct two indices of technology at the business function level.

Intensive The first index reflects the sophistication of the most widely used technology in a business function. The intensive index of a firm j in a business function f is computed as

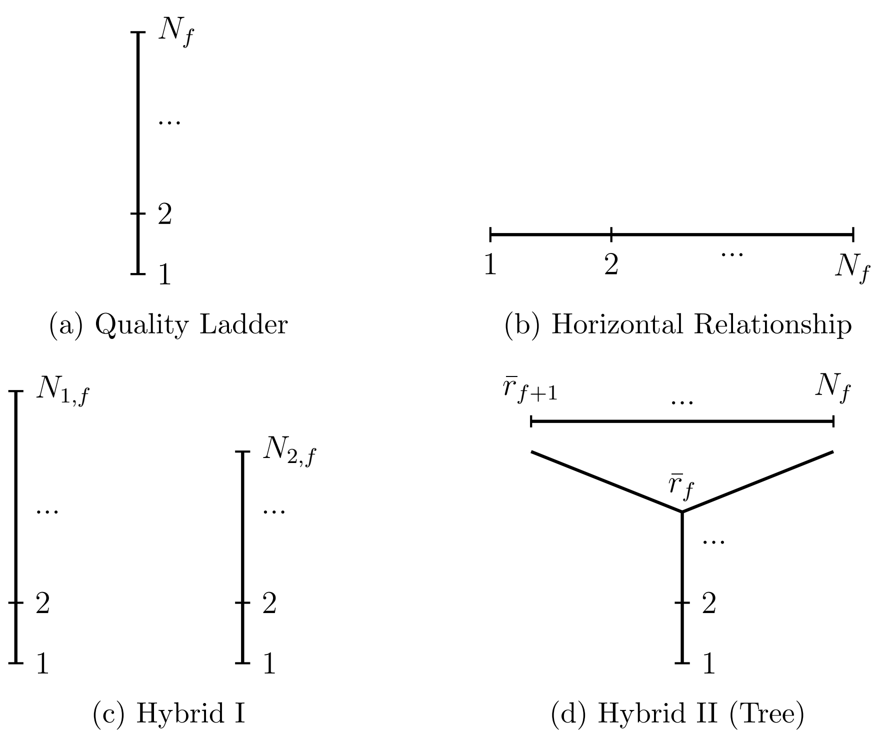
$$T_{f,j}^{INT} = 1 + 4 * \frac{r_{f,j}^{INT}}{R_f} \tag{1}$$

where $r_{f,j}^{INT}$ is the sophistication rank of the technology identified by the firm as being most widely used for the business function, and R_f is the maximum technology rank in the function. Note that we have scaled this index so that it is between 1 and 5.

[16] In a small number of business functions, the technologies covered are used in various subgroups of tasks. For example, in the body pressing and welding functions of the automotive sector, the survey differentiates between technologies used for pressing skin panels, pressing structural components and welding the main body. In cases like this, we construct ranks of technologies for each subgroup of tasks within the business function, and then aggregate the resulting indices by taking simple averages across the task groups.

Extensive The second index we construct measures the sophistication of the array of technologies used to conduct a business function, and we call it EXT (an abbreviation of extensive). In contrast with the intensive, the extensive does not reflect how much each technology is used but it reflects the sophistication of all the technologies adopted and used in production, rather than just the most relevant one. To measure the sophistication of the range of technologies, we must first understand the degree of substitutability between the technologies in the business function. Figure B1 illustrates four possible structures we encounter in the business functions covered by FAT and that differ in the substitutability between their technologies. Panel A depicts a quality ladder or vertical structure (Aghion and Howitt, 1992). In quality ladders there is no productivity gain from using technologies below the maximum sophistication rank employed in the firm, $r_{f,j}^{MAX}$. Therefore, the sophistication of the technologies employed in business functions with a quality ladder structure is $r_{f,j}^{MAX}$.

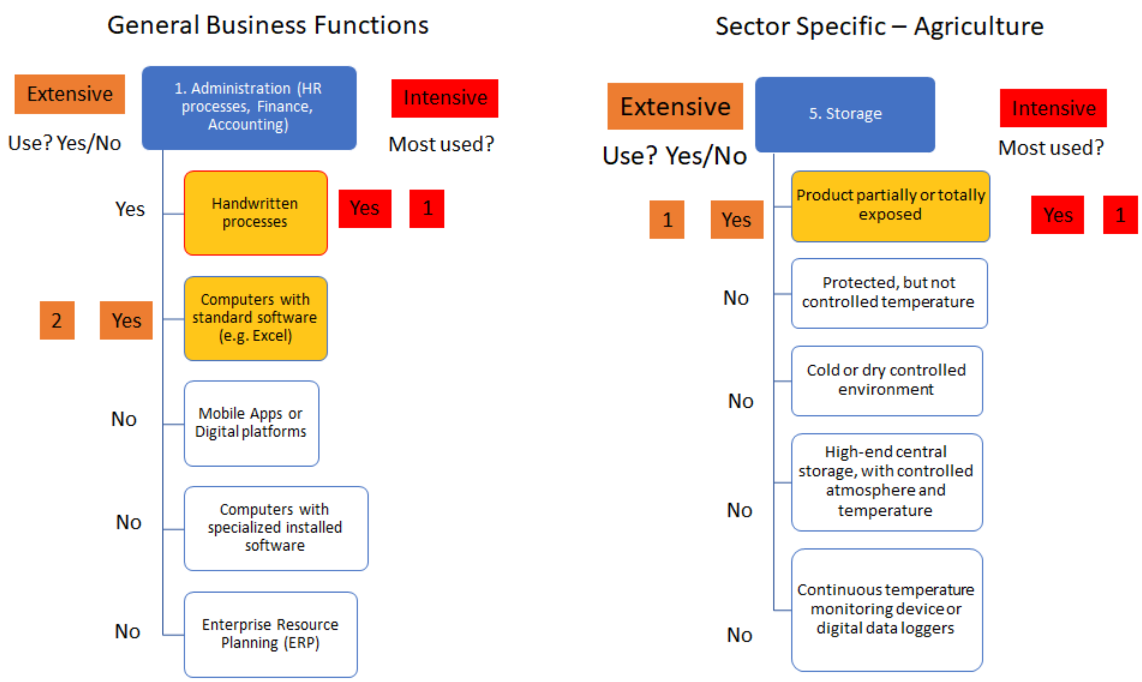
Figure B1: Different technology sophistication structures



The technologies in other business functions may have a horizontal relationship (Romer, 1990), depicted in panel B. In horizontal structures, the use of less sophisticated technologies facilitates the fulfillment of the tasks in the function even conditional on using more sophisticated technologies. For example, in marketing the use of less sophisticated technologies such as face-to-face communications may allow firms to reach some customers that may not be reachable by more sophisticated technologies such as customer relationship management

(CRM) software. The sophistication of the array of technologies used in horizontal structures is measured by the fraction of the possible technologies in the function that the firm uses. Figure B2 shows an example for business and administration processes and for storage in agriculture.

Figure B2: Technology Adoption Index: Example



C Additional tables and Figures

Table C1: Correlates of Technology Use

VARIABLES	**GBF Ext**	**GBF Int**	**SBF Ext**	**SBF Int**
Manufacturing	0.041	0.014	-0.179	-0.271***
	(0.027)	(0.056)	(0.112)	(0.100)
Services	0.074***	0.066	-0.166	-0.195**
	(0.026)	(0.056)	(0.108)	(0.093)
Firm age (6-10)	-0.007	0.010	-0.018	0.031
	(0.024)	(0.022)	(0.059)	(0.047)
Firm age (11-15)	-0.025	0.010	0.022	0.046
	(0.026)	(0.024)	(0.067)	(0.051)
Firm age (>15)	-0.002	-0.008	-0.004	-0.031
	(0.026)	(0.026)	(0.059)	(0.062)
Multinationals	0.030	0.086***	0.107*	0.145***
	(0.026)	(0.020)	(0.063)	(0.048)
Exporting	0.094***	0.045*	0.080*	0.065
	(0.025)	(0.023)	(0.043)	(0.050)
Ln (Employment 2018)	0.036***	0.045***	0.052**	0.038**
	(0.008)	(0.007)	(0.020)	(0.015)
Constant	0.825***	0.464***	0.876***	0.655***
	(0.035)	(0.060)	(0.129)	(0.108)
Observations	1,488	1,488	918	918
R-squared	0.135	0.138	0.094	0.115
Region FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C2: Firm-Level Tech Adoption Index and Value Added per Worker

VARIABLES	(1)	(2)	(3)	(4)
GBF Ext	1.221***			
	(0.293)			
GBF Int		1.119***		
		(0.334)		
SBF Ext			0.367	
			(0.474)	
SBF Int				0.167
				(0.491)
Ln (Employment 2018)	-0.034	-0.033	0.017	0.034
	(0.057)	(0.056)	(0.113)	(0.105)
Constant	6.760***	7.212***	6.982***	7.201***
	(0.420)	(0.370)	(0.549)	(0.493)
Observations	1,409	1,409	874	874
R-squared	0.168	0.160	0.123	0.120
0.128				
Sector FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

Table C3: General Business Functions Heterogeneity

VARIABLES	GBF Ext	GBF Int
Medium	0.226***	0.165***
	(0.059)	(0.035)
Large	0.440***	0.367***
	(0.067)	(0.048)
Manufacturing	0.120*	0.035
	(0.067)	(0.096)
Services	0.176***	0.105
	(0.065)	(0.095)
Constant	2.519***	1.816***
	(0.079)	(0.099)
Observations	1,498	1,498
R-squared	0.092	0.090
Region FE	YES	YES

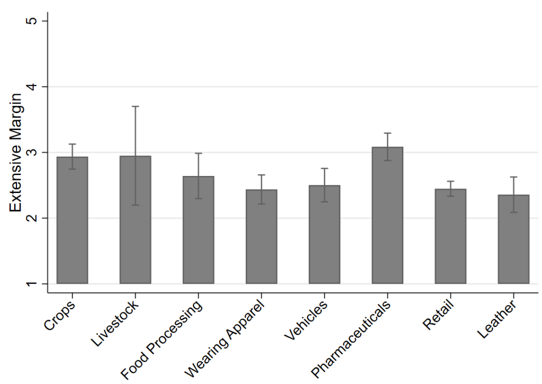
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

Table C4: Sector-Specific Business Functions Heterogeneity

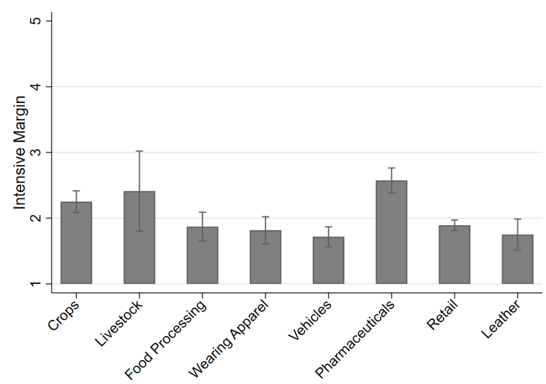
VARIABLES	SSBF Ext	SSBF Int
Medium	0.082	0.082
	(0.101)	(0.101)
Large	0.840***	0.840***
	(0.125)	(0.125)
Livestock	0.013	0.013
	(0.394)	(0.394)
Food Processing	-0.294	-0.294
	(0.184)	(0.184)
Wearing Apparel	-0.499***	-0.499***
	(0.136)	(0.136)
Vehicles	-0.435***	-0.435***
	(0.152)	(0.152)
Pharmaceuticals	0.149	0.149
	(0.138)	(0.138)
Retail	-0.489***	-0.489***
	(0.092)	(0.092)
Leather	-0.464***	-0.464***
	(0.121)	(0.121)
Constant	2.907***	2.907***
	(0.137)	(0.137)
Observations	925	925
R-squared	0.094	0.094
Region FE	YES	YES

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure C1: SSBF - Predicted Values



(a) Extensive SSBF



(b) Intensive SSBF

Note: Panel (a) and (b) provide the coefficients and 95% confidence intervals from regressions, while controlling for size and regions. All estimates are weighted by sampling and country weights.