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Firm-Level Technology Adoption in the State of Ceará in Brazil

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Abstract

This paper uses a novel approach to measure technology adoption at the firm level and applies it to a representative sample of firms in the state of Ceará in Brazil. The paper develops a new measure of technology adoption at the firm level, which identifies the purpose for which technologies are used and the intensive and extensive uses. The survey allows for establishing several new stylized facts for Ceará. First, most firms still rely on pre-digital technologies to perform general business functions, such as business administration, marketing, sales and payments, or quality control. Second, these technology gaps are larger in smaller firms, in the manufacturing sector, with large gaps when it comes to Industry 3.0 and digitalization, and especially large in Industry 4.0 technologies. The paper also presents some evidence that the main challenge to accelerate technology adoption is lack of firm capabilities. Despite the availability of technology extension services in the state, firms are still unaware of the availability of support and unwilling to upgrade technologies.

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1 Introduction

Differences in technology adoption are an important determinant of the widening productivity gap between leader and laggard firms, resulting in large productivity differences across firms and countries. 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). However, despite the importance of technology in explaining income disparities across and within countries, good measures of the use of technology at the firm level are scarce, and confined to a few technologies and sectors. This data gap is especially large in developing countries, which greatly constrains our ability to study the process of technological catch up and the obstacles to adoption and diffusion.

This paper describes the results of implementing a new "Firm-level Adoption of Technology" (FAT) survey implemented in the state of Ceará, Brazil; and identifies some of the key obstacles for the adoption of new technologies faced by those firms. The paper describes with high granularity the level of technology adoption and use across firms and sectors and provides some benchmarks and the relationship between technology adoption and performance.

The FAT survey has been implemented in several countries, covering most regions and sectors within a same country. However, given Brazil's continental dimensions, the survey was implemented only in the state of Ceará, located in the Northeast Region and one of the most populous and poorest states in the country. In terms of GDP per capita, the state is ranked 23rd in the country (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%. Despite the government's effort to decentralize the economy, 43% of the GDP in concentrated in the capital, Fortaleza, with the Metropolitan Region of Fortaleza responding for 64% of the state's GDP. Up to the second half of the 20th century the state's economy depended on the exploration of very few natural resources. In the second half of the century, the federal government through the use of import substitution and other industrial policies allowed the attraction of many industrial investments; especially in the textile, food processing, and footwear industries. Recently, the state was able to attract a new steel mill and other renewable-energy industries, now exporting wind shovels and turbines. In the agriculture sector, irrigation technologies also allowed a surge in the export of tropical fruits.

These large investments coexist with a largely informal economy and an unusually large number of small and unproductive firms. Although productivity growth has been above the country's average (IPECE, 2019) and despite recent positive experiences in education and infrastructure investments, the state still faces many challenges in order to reduce the

productivity gap with more developed parts of Brazil. It is unclear, however, if the bulk of these productivity differences is due to differences in the range of technologies adopted or to other non-technological factors, which highlights the importance of reducing the data gap on technology adoption at the firm level.

The survey implemented in Ceará includes a representative random sample of 711 formal firms with 5 or more employees from the employer-employee census (RAIS), and includes firms in agriculture, industry and services. The FAT survey identifies first 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. 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.

Specifically, in this paper we analyze the adoption of technologies at the firm level in Ceará through three key angles: (1) Standard measures of technology adoption; (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 in non-specific tasks. It includes the access and usage of GPTs such as electricity, phone, computers, internet, cloud computer and digital platforms. We define general business support functions (GBF) technologies as those tasks necessary in any firm, regardless of the sectors they are in, such as business administration, production planning, sales or payments methods. The sector specific business function (SSBF) technologies are those applied for business functions that are industry specific (e.g. land preparation in agriculture industries, or input testing in the food processing industry) and that often refer to sector specific production processes.

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 and Internet, without identify the specific purpose of use. Section 3 describes the new measures of technologies captured by the by the FAT survey and provide its conceptual framework for general and sector specific business functions. Section 4 analyzes the level of technology adoption for general business functions. Section 5 analyzes the level of technology adoption for sector specific technologies. Sections 6 describes some of the key barriers for technology adoption in Ceará, while section 7 analyzes the relationship between technology adoption and employment. The last section concludes.

2 Standard measures of technologies: Use of Industry 2.0 to Industry 4.0 technologies

Standard measures of general purpose technologies (GPTs) can be linked to different stages of technology 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 they 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.[1] 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, Big data analytics and artificial intelligence, 3D printing, advanced robotics, and cloud computing.[2]

2.1 Industry 2.0: Electricity

Practically all firms in our sample have access to electricity but face constant power outages. The availability and reliability of electricity and telecommunications services are important in a firm's decision to adopt a new technology. Table 1 shows basic descriptive statistics of access to electricity, power outages, and alternative sources of electricity. The first two columns show the average and standard deviation. The means are further divided by size groups, sectors, and regions. Three firm size groups are defined by the number of employees: small (5-19), medium (20-99), and large (100+). Almost all firms have access to electricity,[3] but two-thirds experience power outages and only 8% of firms have a generator in house.[4] The variation in power outages is not significant across size groups, but it is significant by sectors, with agriculture and manufacturing having larger incidence of outages. In the case of agriculture, this helps explaining why a larger share of companies in the sector have their own generator.

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

[2] 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 1960s they have been increasingly available in recent years.

[3] Only 1 firm in the service sector does not have electricity connection.

[4] Among firms that have faced power outages, they experienced on average almost four power outages in a typical month, although they usually last less than an hour.

Table 1: Access and Quality of Electricity

Technology	Mean	Std. Dev.	Small	Medium	Large	Agric.	Manufac.	Services	MRF	Other
Having Electricity	99,9%	0,04	100,0%	99,6%	100,0%	100,0%	100,0%	99,8%	100%	100%
Power Outage	65,1%	0,48	67,3%	62,4%	62,3%	82,2%	75,1%	61,6%	61%	66%
Having Generator	7,5%	0,26	3,6%	6,1%	44,9%	46,0%	8,4%	6,4%	6%	8%
Energy: Solar Power	2,0%	0,14	0,0%	4,7%	1,2%	1,4%	2,9%	1,7%	3%	2%
Energy: Fuel	96,6%	0,18	100,0%	93,6%	96,6%	92,0%	95,8%	97,6%	93%	97%
Energy: Wind Power	0,0%	0,00	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0%	0%

Firms across different sizes in Ceará are facing similar challenges associated to the electricity infrastructure; but what seems to differ mostly is their capacity to access alternative source of electricity such as their own generators. Among those firms that have or share generators, the large majority relies on fuel, despite the growing use of wind and solar power in the state.[5] We further divide our sample into two regions, the Metropolitan Region of Fortaleza (MRF) and other regions. The first concentrate over 60% of the state's economy, while the second responds for a relevant share of the footwear industry and the agriculture and livestock sector. Differences in terms of electricity are negligible, while there is a small difference in terms of power outages and use of fuel, where the companies outside the MRF face more power outages and use fuel in 97% of their generators.

2.2 Industry 3.0: ICT

Access to basic ICT technologies is widely available in the state. Table 2 shows the summary statistics of use of ICT general purpose technologies. About 94% of firms use telephone for business purpose, while on average 85% use mobile phones, with this share increasing with firm size. The same pattern is observed in the use of computer and smartphones, with a clear and positive association between access and firm size. The divergence in the adoption of computers and smartphones or tablets for business purpose 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 4 computers per firm, while medium firms have about 13 computers per firm, and large firms have about 113 computers, either desktop or laptop, per firm. The intensive margin differential is also evident in terms of regions, with firms in the MRF having on average a larger number of telephones, mobile phones, and computers. The extensive margin, though, is not significantly different across regions.

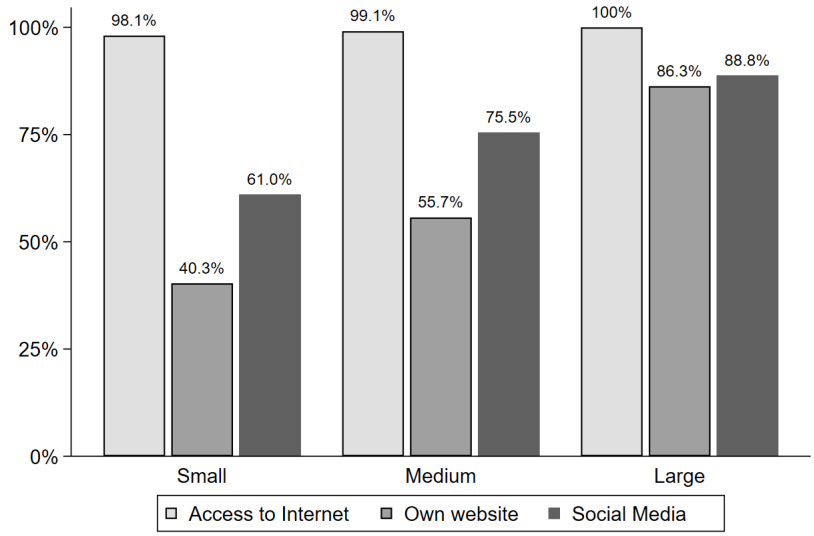
[5] Ceará is one of the states in the country with the largest shares of green energy production, with important developments in wind and solar power.

Table 2: Access to Basic Technologies

Technology	Mean	Std. Dev.	Small	Medium	Large	MRF	Other Regions
Having Telephone	94,3%	0,23	93,9%	94,2%	97,8%	96,3%	94,2%
Having Mobile Phone	84,9%	0,36	78,8%	91,4%	96,4%	84,2%	91,4%
Having Computer	97,9%	0,14	96,2%	100,0%	100,0%	98,5%	100,0%
Having Smartphone	75,1%	0,43	64,8%	85,9%	94,3%	76,1%	85,9%
Having Internet	98,6%	0,12	98,1%	99,1%	100,0%	99,6%	99,1%
Type: Dial Up Internet	1,0%	0,10	1,5%	0,4%	0,5%	1,2%	0,4%
Type: DSL Internet	93,5%	0,25	94,8%	91,4%	94,1%	95,6%	91,4%
Type: Wireless Internet	5,1%	0,22	3,6%	7,5%	4,1%	3,1%	7,5%
Type: BPL Internet	0,0%	0,02	0,0%	0,0%	0,4%	0,0%	0,0%
Acquisition of software	0,3%	0,06	0,1%	0,6%	0,8%	0,1%	0,6%
Number of Telephones	8,77	38,22	2,82	6,75	66,82	10,20	6,75
Number of Mobile Phones	9,37	36,37	2,83	7,15	71,71	10,63	7,15
Number of Computer	15,22	50,13	4,10	13,36	112,99	17,31	13,36
Number of Smartphone	7,02	21,95	2,24	6,74	46,07	7,86	6,74

Most firms in the state also have access to internet; 99% of firms in Ceará has access to internet, with 93% using a DSL connection. There are no significant differences among regions or size groups. On the other hand, there is a clear and positive association between use of more sophisticated digital technologies - having their own website and social media - and firm's size (see Figure 1). Only 40% of small firms have their own website, against over 85% of large firms. A similar pattern is observed in the use of social media.

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



2.3 Industry 4.0

Adoption of key technologies in Industry 4.0 is still very incipient in Ceará, with the exception of cloud computing. As Figure 2 shows, 43.5% of firms make use of cloud computing for business tasks. However, only 4.7% use big data or AI for marketing purposes, and when it comes to fabrication, the use of advances methods for manufacturing is used by only 7.2% of firms and robots by 5.6% of firms. Low rates of adoption of Industry 4.0 technologies are also found in sector specific technologies. For agriculture, only 18% of firms use some form of precision agriculture (IoT) technologies, while only 4% of firms in manufacturing makes some use of 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

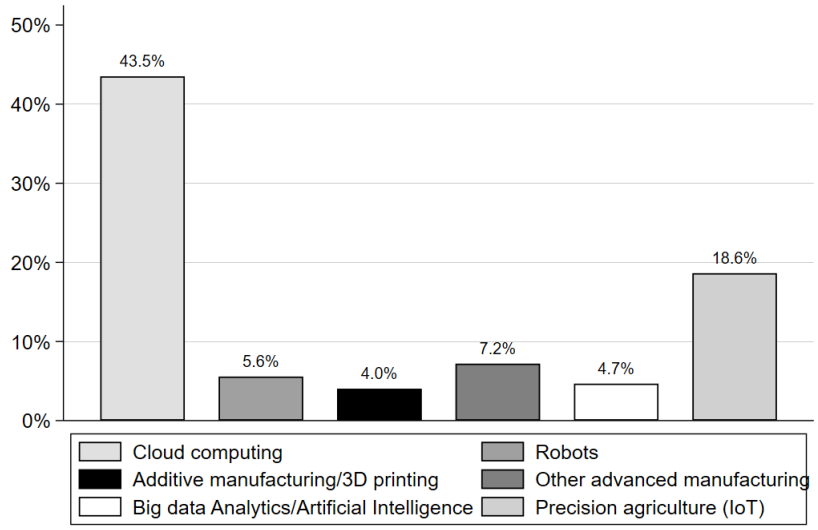
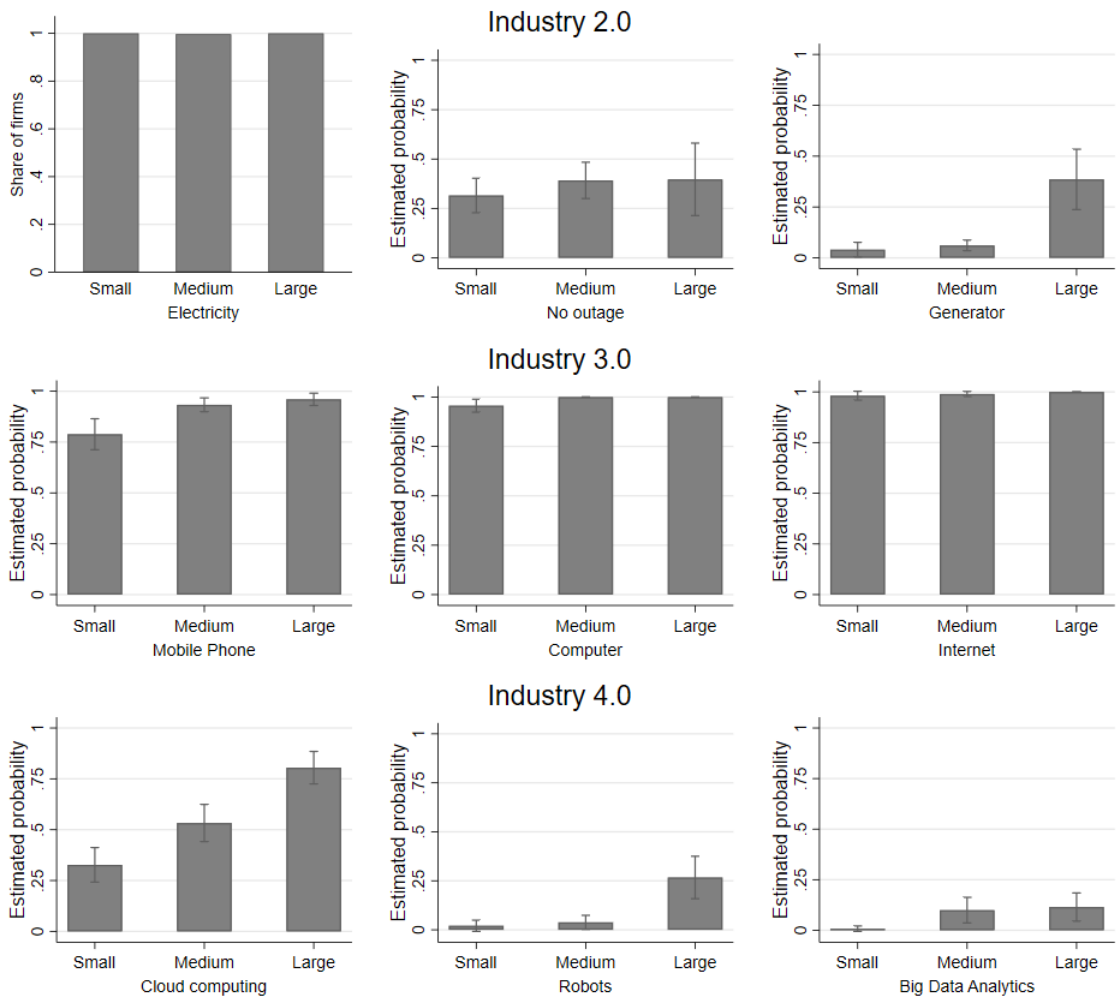


Figure 3 shows the estimated probability of having adopted the different technologies for group size. For Industry 2.0 technologies, the main difference between small, medium and large firms is in the use of generators; a large firm has about 40% probability of using a generator while a small or medium firm has close to 10% probability. For Industry 3.0 technologies there are no significant differences in the use of mobile phones, computers and access to internet. For Industry 4.0, there is a clear and significant relationship between firm's size and the probability of using cloud computing and robots.

Although these indicators provide a general picture on the adoption of a few general-purpose technologies (GPTs), we lack the knowledge of the use of these technologies in different tasks and functions of firms. This is critical since firms can use the internet in many different ways, for example for a few marketing activities or for having full IoTs integrated

production processes; which are likely to result in very differentiated effects on productivity and profits. As a result, it is critical to understand technology use. The next section explores and measures the purpose for which technologies adopted by firms are used.

Figure 3: Summary of General Purpose Technology Adoption in Ceará



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

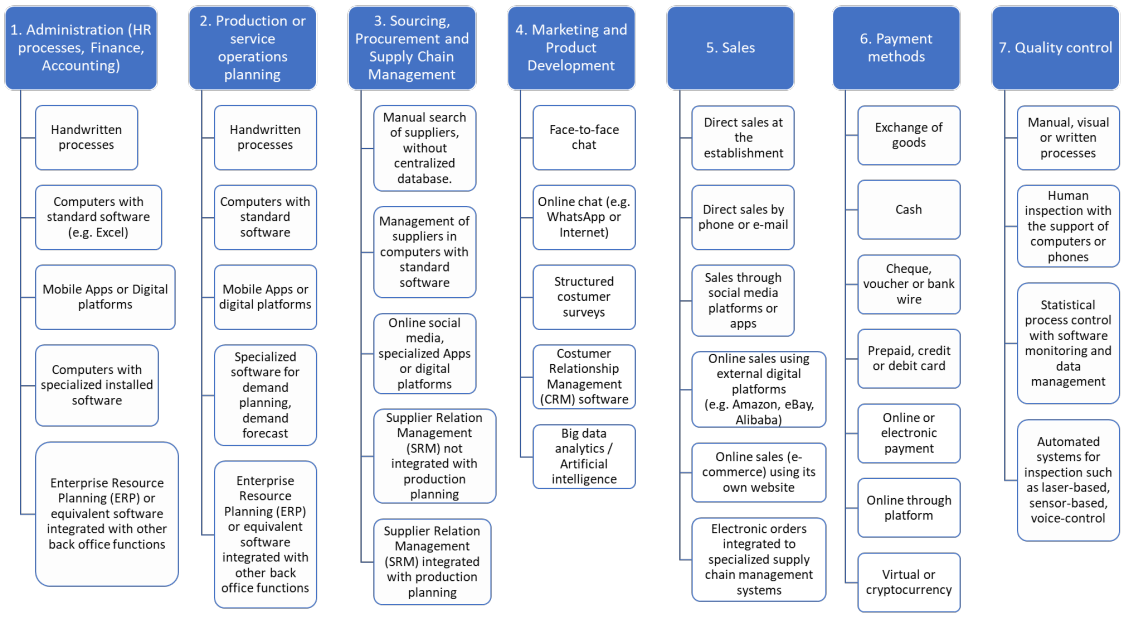
3 New Measures of Technology Adoption and Use: Linking Technologies to Business Functions

In order 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 is 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).

Figure 4: General Business Functions



The Sector Specific Business Functions (SSBFs) are tasks that are associated with the core production or service provision activity and varies across sectors. The FAT survey in Ceará 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 basic level of technology used and 5 reflects the most sophisticated level 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.[6]

Table 3 compares the different technology indices for the State of Ceará, Vietnam, and Senegal.[7] While Ceará performs as expected better than the other two countries, firms in the state are nevertheless far from the frontier in the adoption of technologies. At the intensive margin, Ceará stands less than halfway to the frontier with an index of 2.49[8] and 1.92 when it comes to SSBFs. As expected, the distance to the frontier is higher at the intensive margin. Overall, the gap between Senegal and the state of Ceará is between 36% and 16% across the different indices, highlighting that the state uses very basic sector specific technologies.

[6]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 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 used. 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.

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

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

Table 3: Cross-Country Difference in Technology

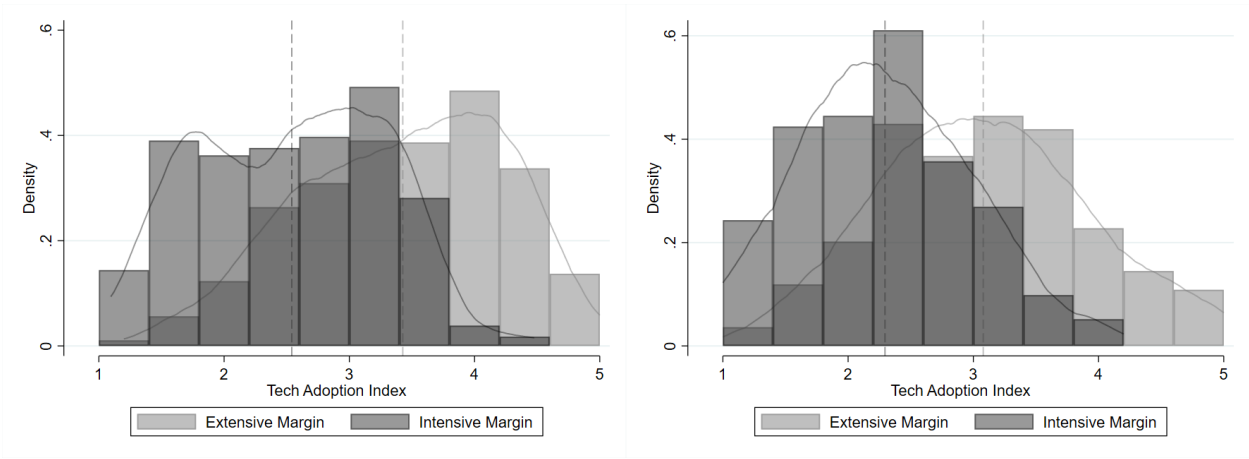
	General Business Function		Specific Business Function	
	Extensive	Intensive	Extensive	Intensive
Average	2.67	1.90	2.30	1.66
Ceará (Brazil)	3.35	2.49	2.75	1.92
Vietnam	2.75	1.92	2.55	1.80
Senegal	1.92	1.29	1.59	1.27
Gap: BR - SN	1.43	1.20	1.16	0.65
Relative Gap**	36%	30%	29%	16%

Source: Cirera et al. (2020)

Note: Relative gap is (Brazil-Senegal)/Maximum Gap(4).

Despite the differences in the averages across countries, an important finding of our analysis is the significant heterogeneity across firms. Figure 5 presents the distribution of the technology index for GBFs and SSBFs in Ceará across firms. The distribution shows that a large share of firms still rely on basic technologies to perform either GBFs or SSBFs. Yet, those firms with higher level of technology measured by the index we propose also have better performance in terms of productivity, measured by value added per worker (Figure 6). [9]

Figure 5: Technology Adoption – Firm-Level Distribution



(a) General business function

(b) Sector-specific business function

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

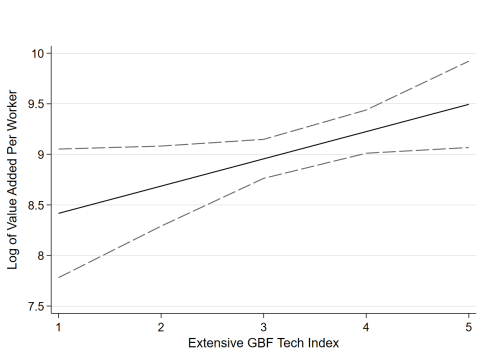
While these results do not suggest any causal relationship between technology and per-

[9]The elasticity of the technology index with respect to value added per worker is 0.77 and 0.74 for the extensive and intensive margin GBFs, respectively. Table C2 in the appendix provides the full results for these estimates.

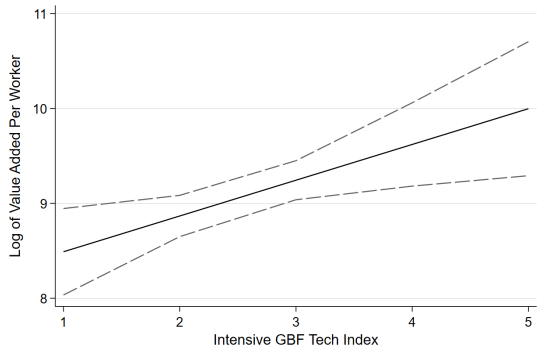
formance, they are consistent with previous literature. Although further investigation is needed to determine the causal relationship between technology adoption and performance, available evidence suggest that adopting technology pays off. Easterly and Levine (2001) and Comin and Hobijn (2010) and Comin 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.

Sections 4 and 5 provide more details on the heterogeneity of adoption for general and sector specific functions.

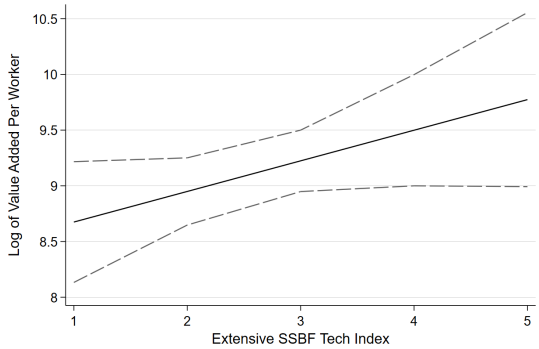
Figure 6: Firm-level Tech Adoption Index and Value Added per Worker



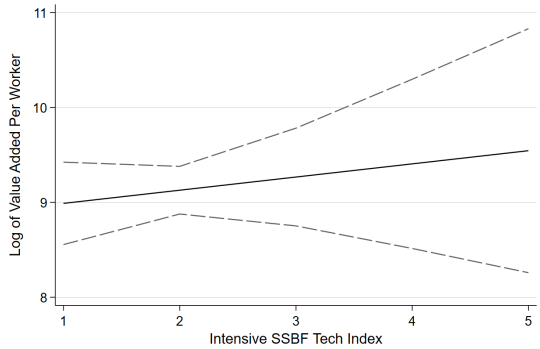
(a) Correlation between extensive GBF index and labor productivity



(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.

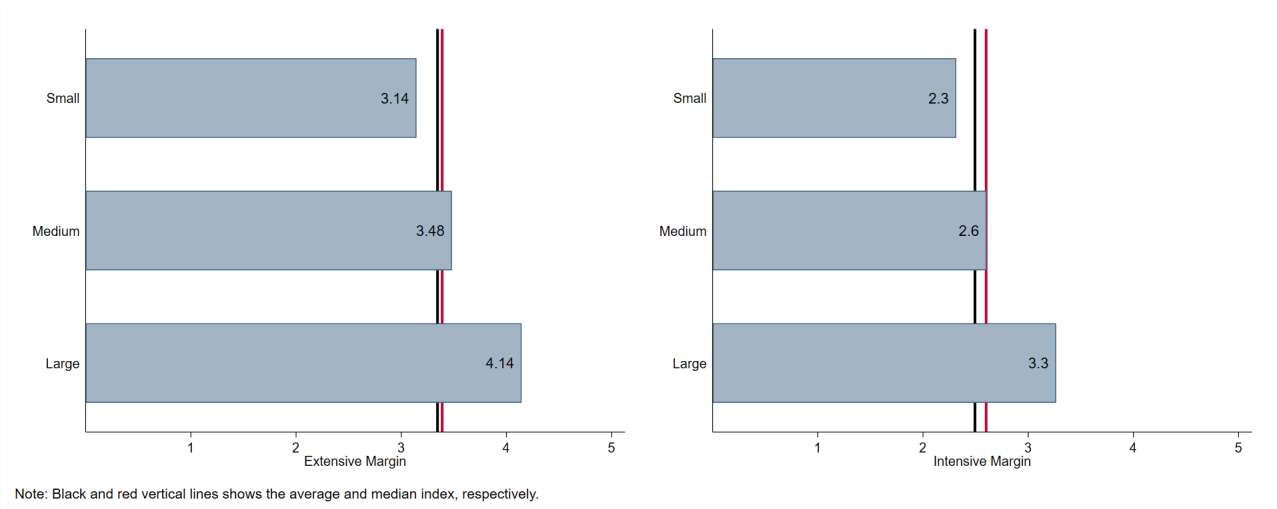
4 Technology Use in General Business Functions (GBF)

The GBFs are commonly needed business functions across all firms, irrespective of the industries they are in, and therefore their adoption 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.

4.1 The relationship between technology use and firm size

The technology gap to the frontier at the intensive margin in Ceará is significant, especially among small and medium size firms. Figure 7 shows the average technology indices for the intensive and extensive margin by firm size, with the black and red vertical lines indicating the average and median index for the state, respectively. Once again there is a clear and positive association between the size groups and the sophistication of the technology use index, both for the extensive and intensive margin. Larger firms in Ceará are closer to the frontier in terms of technology use in GBFs. However, even large firms show a significant gap compared to the frontier (5 would be frontier technology in all GBFs). It is also clear that the gap is larger for the intensive margin, which shows that even though firms are adopting more sophisticated technologies, the use of these technologies is still limited in some business functions.

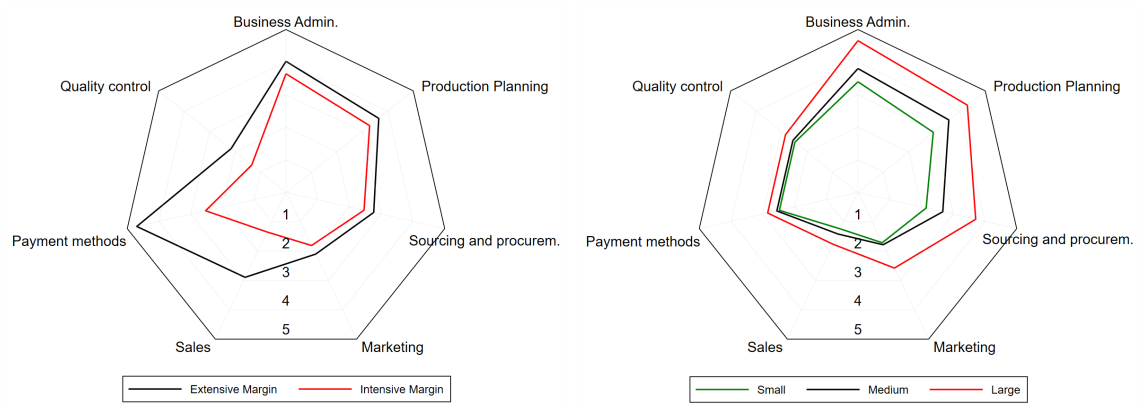
Figure 7: GBFs: Extensive and Intensive Margin in Ceará by Group Size



There are significant differences between the extensive and intensive margins across business functions. Even though the extensive and intensive indexes are similar in some functions, such as marketing and business administration, there is a significant

gap in others, particularly in the case of payment methods and sales (see Figure 8). The intensive margin index suggests that on average the use of new technologies is limited across general business functions. However, panel B shows that the gap is largely explained by size group differentials, as large companies are closer to the frontier in the case of Business Administration, Production Planning, and Sourcing and Procurement.

Figure 8: General Business Functions in Ceará

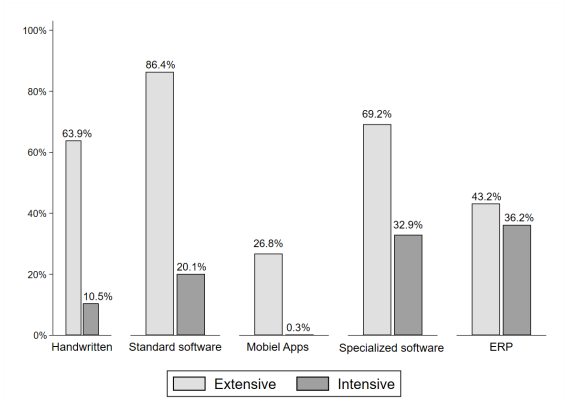


(a) Extensive and intensive GBF (b) Intensive GBF by size group

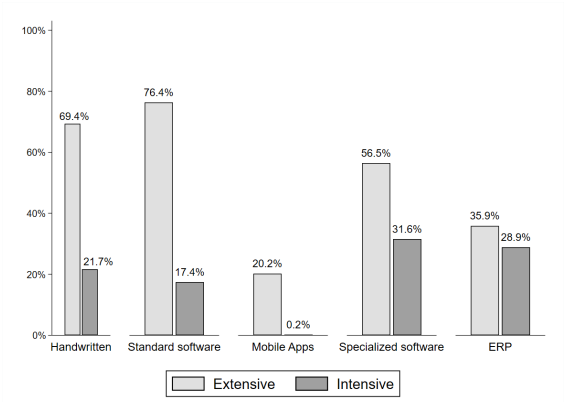
Note: Each line represents the index average across firms for each business function.

Firms in Ceará lag behind especially in the technologies used for sales, marketing and quality control. Looking at the intensive margin, the average firm in the state uses technologies that are far from the frontier in these three business functions. In the case of marketing this gap is also large in relation to the extensive margin. On the hand firms are more advanced in the use of technologies for payments and business processes administration, such as HR. Figure 9 shows more detail in the use of these technologies. It is clear, for instance, that even though firms use more sophisticated sales methods, such as digital platforms and electronic orders, most of their sales are carried through basic technologies. Costumer information technologies are very limited in the state, with most firms relying on face-to-face and online chat as their main source of information. More advanced technologies are used in business administration processes, where a significant share of firms have adopted specialized software and ERP as their main technologies, particularly by large firms.

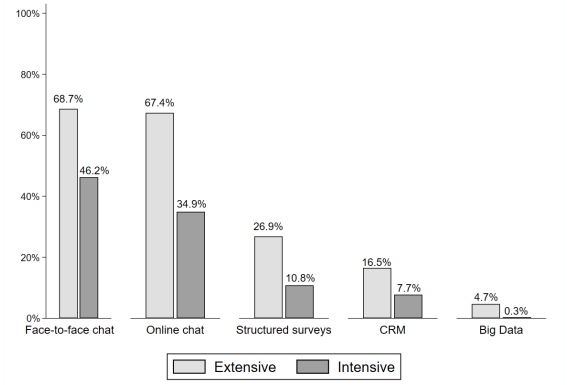
Figure 9: Share of Firms Using Technologies Applied to General Business Functions



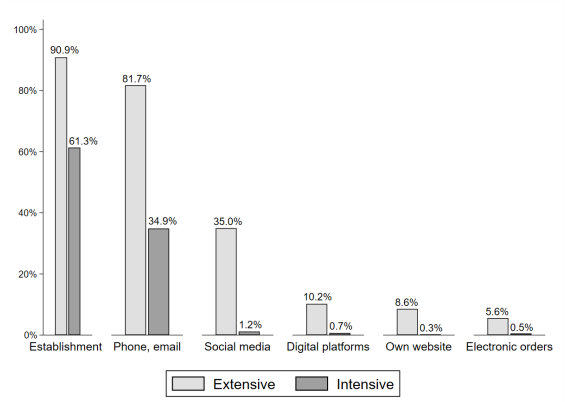
(a) Business administration processes related to account, finance, and HR



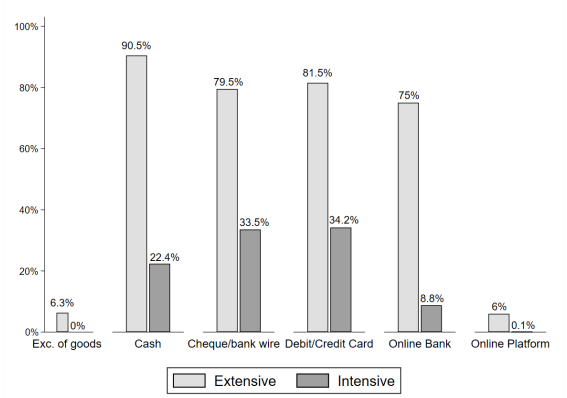
(b) Production or service operations planning



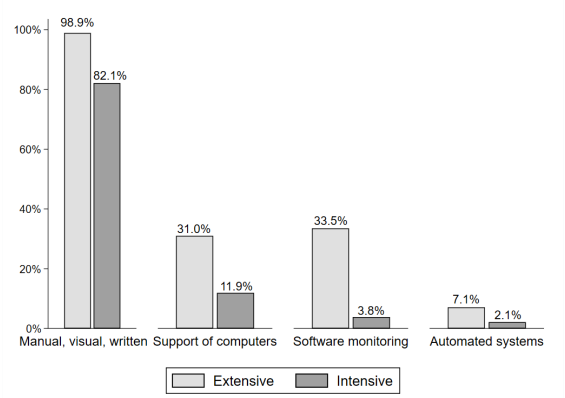
(c) Customer information for marketing and product development



(d) Sales methods



(e) Payment methods



(f) Quality control inspection

4.2 Technology use by sector

Agriculture and services are the sectors with the highest adoption indexes at both the extensive and intensive margins. Looking across sectors, Table 4 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. Looking at the intensive margin - mostly used technology - agriculture is the sector using more sophisticated technology followed by services and then industry. The services sector, however, has a higher index when it comes to general business functions at both the intensive and extensive margin. The results highlights a wider technological gap in manufacturing.

Table 4: Cross-Sector Differences in Technology

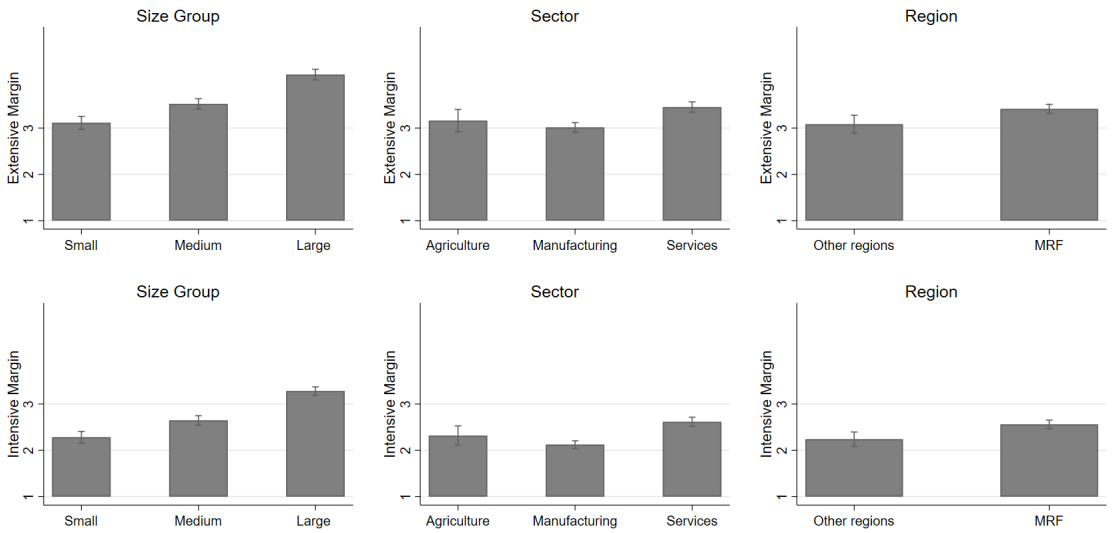
	ABF			GBF			SSBF		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Intensive margin	2.54	2.13	2.38	2.33	2.16	2.60	2.84	1.93	1.90
Extensive margin	3.25	3.03	3.18	3.17	3.05	3.43	3.38	2.97	2.61

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

Figure 10 shows the conditional predictions of the GBFs by firm type, sector and location. When controlling for other factors, the correlation between size and technology sophistication persists. For the sectors, however, when controlling for firm size, age and location services have larger coefficients than agriculture and manufacturing. The differences between regions are small.

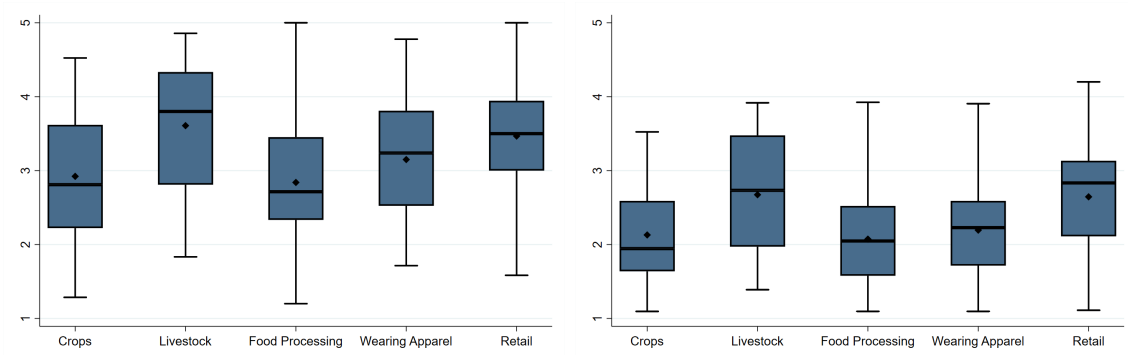
Livestock and Retail use more advanced technologies for general business purposes. Focusing on those sectors where the sample was stratified, Figure 11 shows box plots figures for each sector and for both extensive and intense margins. The figure suggests that variance within sectors is larger for the extensive margin in comparison to the intensive margin, even when controlling for sector differences. This finding suggests that even though there is a larger variance in terms of firms reporting using more advanced technologies, the most commonly used technology is usually more similar across companies. Panel A in Figure 11 also suggests that the median of firms in the Livestock sector are using the most advanced technologies when measured by the extensive margin index. At the intensive margin, however, the median retail firm uses more sophisticated technologies.

Figure 10: General Business Functions in Ceará - Heterogeneity



Note: Figure shows the predicted probability 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.

Figure 11: Sector GFB Index



(a) Extensive margin (b) Intensive margin

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

5 Sector-Specific Business Functions

Sector specific business functions refer to functions and tasks that are specific to different sectors. These are related to the fact that production processes and task are different depending on what is being produced. These business functions are specifically related to core production processes or service provisions. This section discussed adoption of these sector specific business functions (SSBF) in the state of Ceará, for those sectors included in the survey.

Agricultural firms in Ceará have the highest technology indices when it comes to sector specific technologies. Table 4 shows much higher sophistication in technology use in agriculture than in manufacturing or services, and the gap is much larger than for general business functions. This suggests some positive link between sectors of comparative advantage and the extent of adoption in the state. It also emphasizes the larger gap in manufacturing.

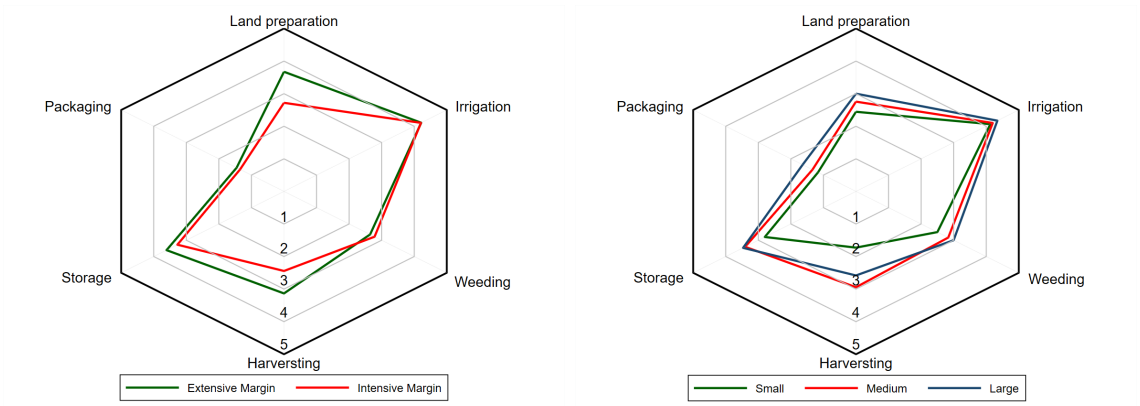
5.1 Agriculture

This section explores the patters of technology adoption and use for two sub-sectors in agriculture, crops and livestock.

5.1.1 Crops

Except for irrigation and storage, the sophistication of the technologies used for agriculture is low in both the extensive and intensive margins. Despite the water and soil restrictions in the semi-arid region, the state of Ceará has become an important producer of fruits in the past years. This is clearly reflected in the sector specific business functions, with a high average index for irrigation in both extensive and intensive margins. On the other hand, technology adoption is more limited in the other core sector specific functions, as in the case of packaging and harvesting.

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.

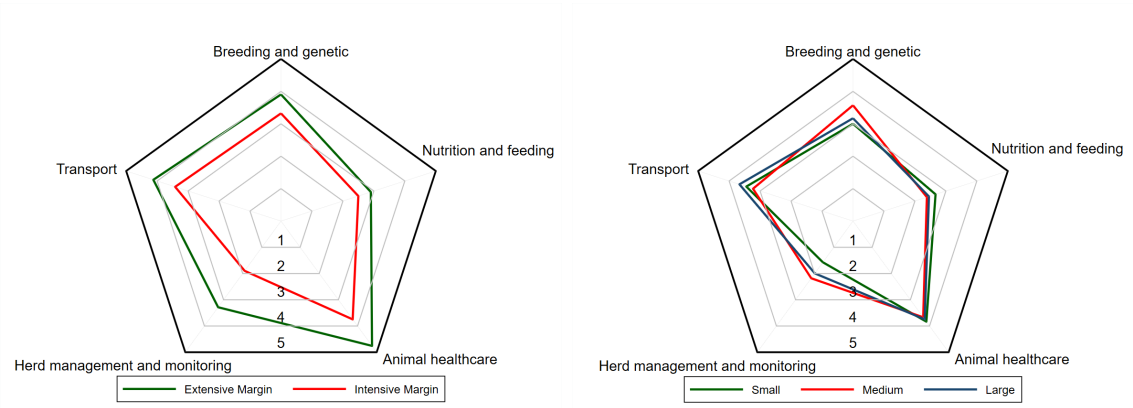
For tasks related to packaging, storage, harvesting, and weeding and pest management, the level of technology is close to 3 in the intensive margin, halfway to the frontier. About 70% of farms use mechanical applications of organic herbicides for

weeding and pest control as the most frequently used technology, while more than 30% of farms still use manual harvesting, training or pruning. Overall, these results suggest that farms in Ceará are still relying mostly on basic technologies to perform these tasks. This fact suggests heterogeneity in the level of technology used across business functions within firms. The small gap between the extensive and the intensive margins of technology in irrigation suggest that this is a business function in which firms adopt intensively the most advanced technologies. In fact, for 63.6% of farms drip or localized irrigation is the most used technology, while 36.4% rely on automated systems.

5.1.2 Livestock

The sophistication of technologies adopted in the livestock sector shows significant variation. The intensive margin index varies from 1.8 for herd management and monitoring to 3.7 for animal healthcare, suggesting large variance across business functions. The intensive margin index suggests that animal healthcare is a business function in which farms are intensively adopting a more advanced technology; 51% of farms make use of disease medication, the most advanced technology. On the other hand, nutrition and feeding and herd management and monitoring are largely based on basic technologies; 51% of farms rely on human monitoring for herd management and about 60% use manufactured or mixed food for animal nutrition. In the case of transport, 77% of farms use motorized vehicles, although 11% still use manual transport and 11% use non-motorized vehicles. Variance is large for animal breeding and genetic. An important share of farms, about 23%, are using selective breeding as the more often used method for breeding. However, 37% are using either breed substitution (14%) or inbreeding or crossbreeding (23%), the most basic technologies.

Figure 13: Livestock - 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.

There is no significant difference in technology adoption across size groups. Panel B of Figure 13 shows the intensive SSBF by size group. The results indicate that technology adoption in the livestock sector in Ceará is very similar irrespective of size, exception being herd management and monitoring, in which small farms show a larger gap. However, the figure is clear in showing that even large farms in the state are far from the frontier in most business functions.

5.2 Manufacturing

5.2.1 Food Processing

In the food processing sector, the extensive and intensive margin adoption indices are low. Food processing is one of the largest industries in Ceará. In 2018, food processing industry employed almost 36,000 workers, the third largest industry in the state. Figure 14 shows significant gaps between the extensive and intensive margin, indicating that most firms rely more intensively on very basic technologies, with indices ranging from 1.95 to 2.6 in the intensive margin. For instance, about 80% of the establishments rely on the review of supplier testing, among the most basic procedures. For mixing, blending, and cooking, firms are using machines, but most of them use manually operated as the main technology. About 37% of firms use "manually-operated machine" in the intensive margin, while 41% of firms still rely on fully manual processes. For packaging, 32% of firms still rely on manually operated process, while 37% use human operated machines as the most frequently used technology. For food storage, "ambient conditions in closed building" is the most used type for about 57% of firms; only 20% use fully automated climate - the most advanced.

Figure 14: Food Processing - SSBF

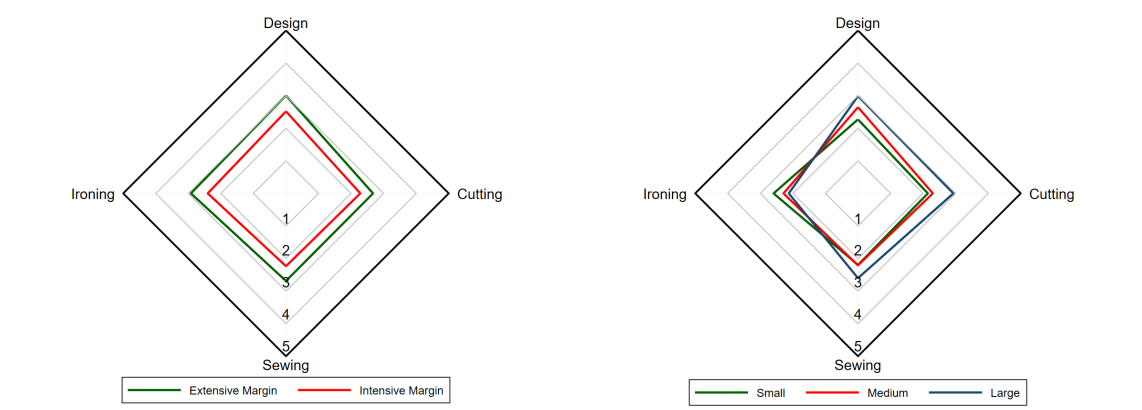
(a) Extensive and intensive SSBF (b) Intensive SSBF by size group

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

5.2.2 Wearing apparel

For wearing apparel, the majority of firms still rely on manual design and manual cutting, machines manually operated for joining parts, and manual ironing as the most used technologies. Figure 15 shows that on average firms use very basic technologies, with average extensive index ranging from 2.67 for cutting to 3 for design. For cutting, 54% still rely mostly on manually operated machines. Also, 12% use manual cutting. The same pattern is seen in the sewing and ironing processes, with 58% of companies using manually operated machines for sewing and 41% relying on electric high-pressure steam for ironing as their most frequently used technologies. In the intensive margin, differences across size groups are small, with larger firms using on average more advanced technologies for cutting, sewing, and design. On the other hand, small firms use more advanced technologies for ironing.

Figure 15: Wearing Apparel - SSBF



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

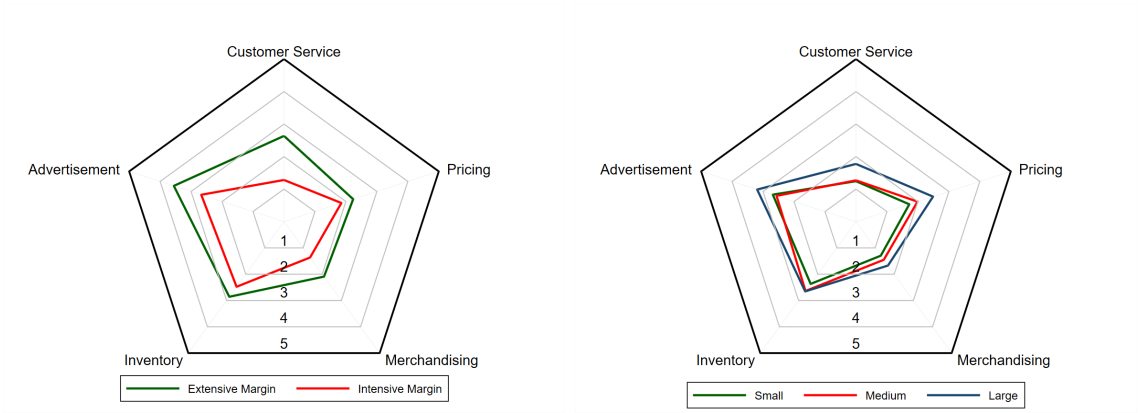
Note: Each line represents the index average across firms for each business function.

5.3 Services - Retail and wholesale

In retail, on average, firms are still relying mostly on manual technologies for customer services, pricing, merchandising, inventory, and advertisement. Only 4% of firms are using social media for costumer services as the most frequently used technologies. In the intensive margin, almost 95% of firms provide the services at the premise (71%) or by phone (23%). In other business functions, such as pricing strategies, 38% uses "manual cost" as the most frequently used technologies, followed by dynamic pricing systems (26.8%); 67% relies on manual selection as the most used technology for merchandising, while 24%

are using category management tools in the intensive margin. Panel B in Figure 16 shows that large firms are adopting more advanced technologies, particularly for customer service and pricing. Yet, the gap to the frontier is still large in the state, irrespective of size.

Figure 16: Retail and wholesale - SSBF



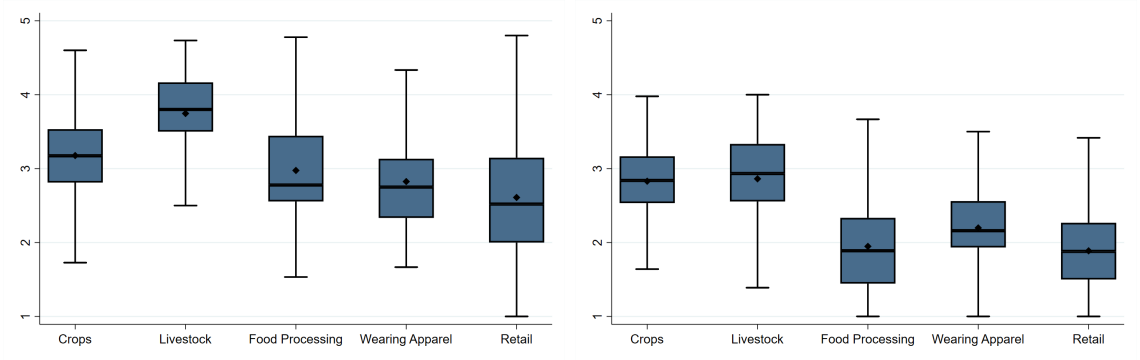
(a) Extensive and intensive SSBF (b) Intensive SSBF by size group

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

5.4 Cross-sector differences in sector-specific technologies

On average, agriculture sectors, especially livestock firms use more advanced sector specific technologies than in other sectors. Although sector specific functions are not directly comparable, our technology index allows to use similar scales in terms of the distance to each relative frontier. Figure 17 shows the differences within and between sectors in SSBFs, and show some important facts about technology adoption and use in the state. First, it suggests that on average Livestock firms are using the most advanced sector specific technologies in the state, both for the extensive and intensive margins. Interestingly, the variance within the Livestock sector is also the smallest, indicating very similar technologies across companies. Technology use appears to be higher in some sectors of more comparative advantage. Second, the within sector variance is larger for Food Processing and Wholesale and Retail. In the specific case of Food Processing, in which the state has some large and very competitive companies that supply the rest of the country, these firms coexist with firms that use very basic technologies. In the extensive margin, this pattern is even clearer in the Wholesale and Retail, with the first quartile showing an index ranging from 1 to 2.

Figure 17: 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

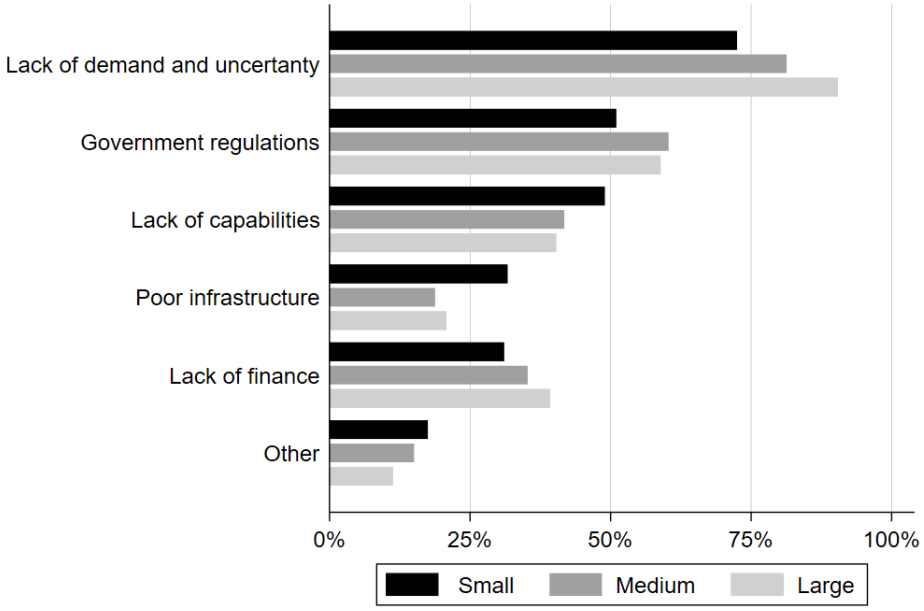
A critical question for policy is what are the main barriers that constrain the adoption of more sophisticated technologies among firms. The survey provides some detailed information to respond to this question.

6.1 Perceived barriers to adoption

A large share of firms reports lack of demand and uncertainty as the key perceived obstacles for adopting better technologies. The survey asks firms about their top three obstacles to adopt technology. Figure 18 describes the share of firms reporting obstacles by firm size group. 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,...). Lack of demand and uncertainty is the main obstacle for all firms, followed by government regulations. Interestingly, although large firms face lower interest rates, they reported financial constraints as an important obstacle more frequently than small and medium firms. Almost 50% of small firms see lack of capabilities as an important obstacle, and around 30% of firms, especially small firms, see the cost of energy and internet as a significant obstacle to technology adoption; a less relevant obstacle to medium and large firms.

The perceived barriers and obstacles do a poor job in explaining the technology indices, which remain largely unexplained. We estimate linear regression models to analyze the statistical association between the level of technology adoption and the perceived obstacles, while controlling for firm size, sector, and region (see Table 5). The results show little significance of these perceived obstacles, which even controlling for size

Figure 18: Perceived Obstacles for Adopting Technology by Firm's Size



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

and sector can only explain between 35% and 24% of the variation in technology indices. For GBFs, only lack of demand and uncertainty seems correlated with the index, with a puzzling positive sign. For SSBFs only lack of capabilities and marginally poor infrastructure show a significant negative correlation. This suggest that other unobserved factors are driving technology adoption and use, but also likely low quality of these perceived obstacles as true measures of barriers. As a result, in what follows we focus on a set of factual variables and analyze their role in explaining adoption and use.

Table 5: Perceived Obstacles and Reasons for Adopting Technology

VARIABLES	GBF Ext	GBF Int	SSBF Ext	SSBF Int
Lack of capabilities	-0.038	-0.041	-0.085	-0.169***
	(0.034)	(0.044)	(0.062)	(0.056)
Government regulations	-0.029	-0.007	-0.010	-0.098*
	(0.031)	(0.039)	(0.064)	(0.053)
Lack of finance	0.014	-0.010	0.008	-0.061
	(0.032)	(0.040)	(0.055)	(0.052)
Lack of demand and uncertainty	0.113**	0.100*	0.065	0.006
	(0.046)	(0.059)	(0.066)	(0.063)
Poor Infrastructure	-0.059	-0.088*	-0.139**	-0.109
	(0.039)	(0.049)	(0.068)	(0.067)
Other	-0.010	0.000	0.040	0.004
	(0.032)	(0.055)	(0.066)	(0.053)
Ln (Employment 2018)	0.095***	0.121***	0.103***	0.077***
	(0.011)	(0.014)	(0.024)	(0.025)
Constant	0.619***	0.212*	0.765***	0.914***
	(0.090)	(0.111)	(0.119)	(0.125)
Observations	702	702	474	474
R-squared	0.329	0.347	0.245	0.236
Sector FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES

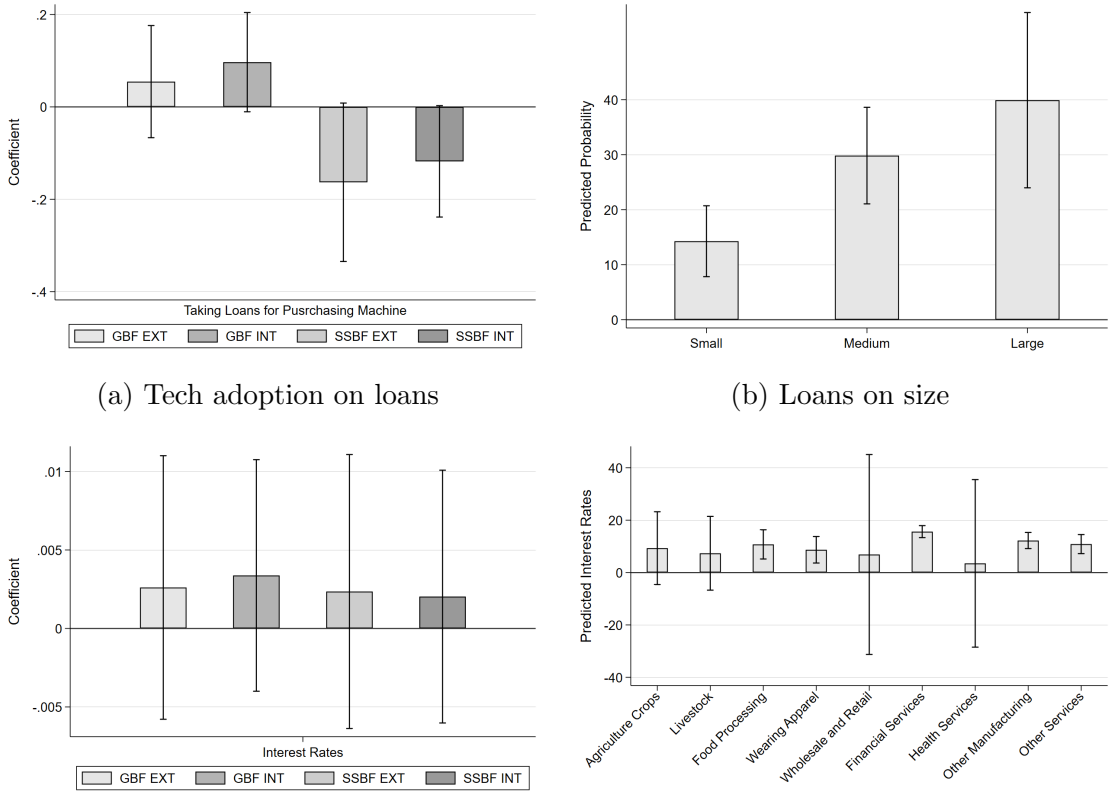
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

6.2 Financial Constraints

Access to finance is an important barrier to the adoption of technologies. By studying a model of establishment dynamics with a producer-level data, Midrigan and Xu (2014) found that financial frictions distort firm entry and technology adoption decisions, which results in lower level of aggregate productivity. Cole et al. (2016) provides a dynamic state model to explain that the efficiency of the financial system determine 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).

Access to finance is not a key barrier to adoption in Ceará. Figure 19 panels (b) and (d) describe the prediction for the two variables by firm size and sector, and controlling for other observables. Small firms have less than 20% probability of having a loan, compared to large firms that have 40% probability. By sector, and controlling for other factors, financial services, food processing and other manufacturing firms appear to face larger interest rates on their loans. Figure 19 panels (a) and (c) present the predictions of our measures of financial access - whether firms took loans and what interest rate - on the index of technology and

Figure 19: Loans for Purchasing Machines/Software and Interest Rates



(a) Tech adoption on loans

(b) Loans on size

(c) Tech adoption on interest rate

(d) Interest rate on 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.

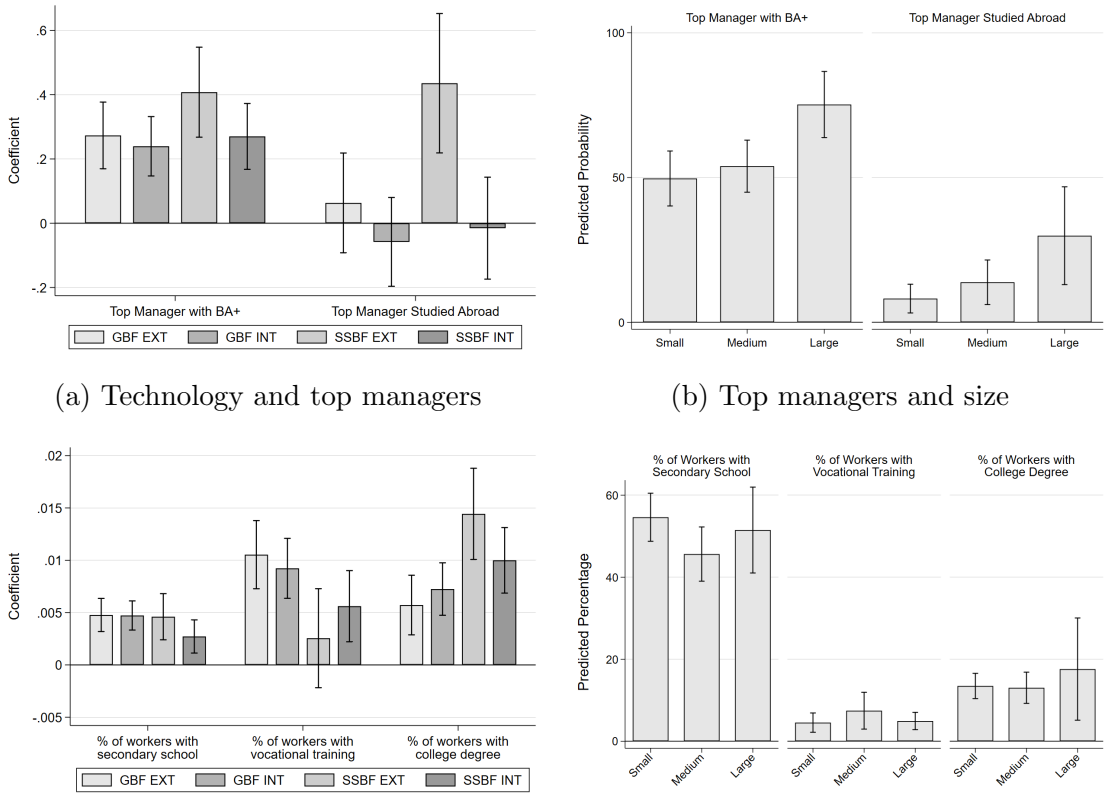
the incidence of these variables by firm size and sector - panel (b) and (d). Having a loan is positively correlated with the adoption of GBFs. On the other hand, there is a negative relationship between SBFs and taking loans. But none of the coefficients is statistically significant from zero. In the case of the interest rates paid in existing loans, the results are also not statistically different from zero for all measures of technology adoption. This is consistent with the perceptions that ranked access to finance as a low barrier to adoption.

6.3 Firms capabilities

6.3.1 Management quality and skills

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 on technology adoption and use.

Figure 20: Human Capital



(a) Technology and top managers

(b) Top managers and size

(c) Technology and Workers

(d) Workers and 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, BA+ 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.

Skills, especially those of the manager matter for technology adoption, especially for GBFs Figure 20 shows the results of a similar exercise than before showing the

predictions associated to human capital measures. Panels (a) and (c) focus on the correlation between the human capital of managers and workers and technology use. Having a manager that has studied at least a BA does not increase the technology index very much, between .2 and .04. On the other hand, if the manager studies abroad the impact on most functions is not significantly different from zero; the exception is the SSBF Ext, for which there is a coefficient of 0.4. Similarly, the effect of having a larger percentage of workers on vocational or secondary education does little to increase the sophistication of technology use. The impact, albeit very small is more visible with increases in the percentages of workers with university education. When looking at the incidence of these human capital characteristics across types of firms, having managers that have studies abroad is uncommon, and more probable in large firms. Similarly, the probability of having more workers with college degrees is larger in larger firms as expected.

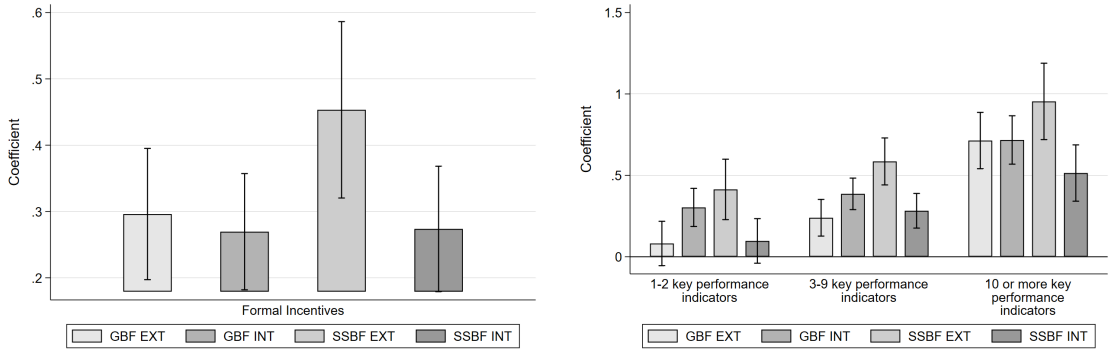
Managerial quality is highly correlated with technology adoption. The recent introduction of the World Management Survey (WMS), initiated by Bloom and van Reenen (2007, 2010), has permitted a quantum leap in the measurement of management practices and their implications for firm performance. The FAT survey collects information on a couple of structured management practices that allows us to proxy management quality and analyze the relationship with technology adoption. The questionnaire ask if firm's make use of formal incentives and the number of performance indicators they use. We use these two measures and compare then with the technology adoption indices. Figure 21 shows that firms using formal incentives to workers have a higher index for both general and sector specific business functions; in the case of SSBF, the adoption of formal incentives is correlated with having .45 higher extensive index. Panel B also suggests that this correlation increases further with more performance monitoring indicators; with those firms monitoring more than 10 indicators having .5 point of more sophistication use of technology.

6.3.2 Awareness, information and overconfidence

Lack of capabilities, in terms of knowledge, information, and technical skills can significantly restrict technology adoption. Flows of information and skills with MNEs and other firms that can facilitate adoption are larger among larger firms and in the agriculture sector. These tend to be 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).

In Ceará being part of a GVC and the experience of the manager and CEO are correlated with more sophisticated use and adoption of technologies. Figure 22

Figure 21: Management Capabilities and Technology Adoption

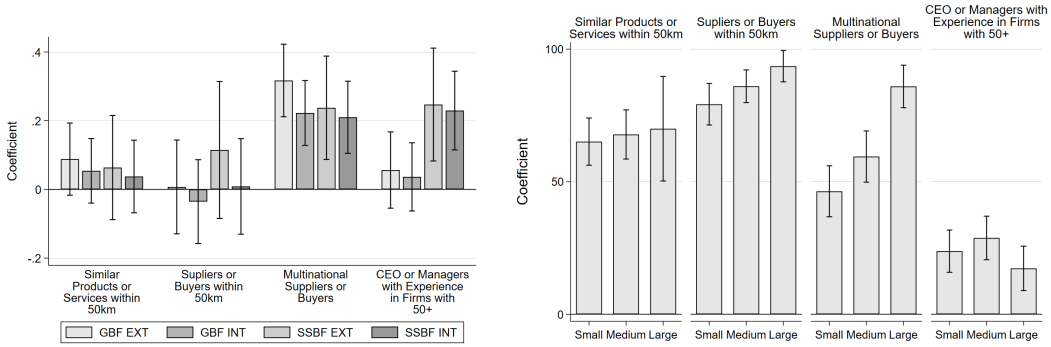


(a) Technology and formal incentives (b) Technology and performance monitoring

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.

panel (a) shows that being part of a GVC is associated with between .3 and .2 higher technology index, and this is more common among larger firms (panel (b)). The previous experience of the manager or CEO in large firms is associated with higher technology only for SSBFs (.2).

Figure 22: Awareness and Information



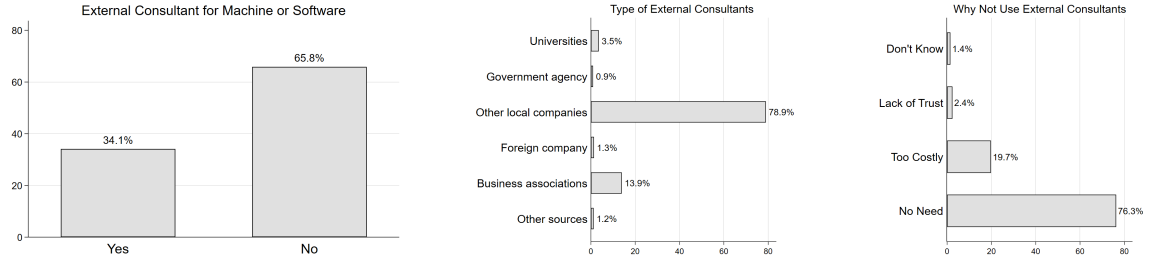
(a) Technology and information (b) Information and formality

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.

A majority of firms in the state do not rely on external knowledge when purchasing new machinery or software, and the use technology extension is very

limited despite its large availability. Shin (2006) found that getting an 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. In Ceará, however, only 34% of firms have used external consultants for this purpose, of which 79% relying on other local companies (see Figure 23). Business associations in Brazil have an important role in technology dissemination and adoption. Brazil's "Sistema S" offers technical education, business education, and specialized consultancies aiming to modernize processes, practices and methodologies in manufacturing and services. The infrastructure for technology extension in agriculture is also large. In Ceará, about 14% of firms used business associations as a source of technical assistance when purchasing equipment and software. Meanwhile, only 3.5% of companies have worked with universities for external consultancy, suggesting the need to improve university-firms collaboration. Among those firms that have not used external consultants, 19.8% find it too costly, but the most common reason reported for lack of access external consultants is "no need" (76%); which in some cases can be suggestive of overconfidence.

Figure 23: Access to External Consultants

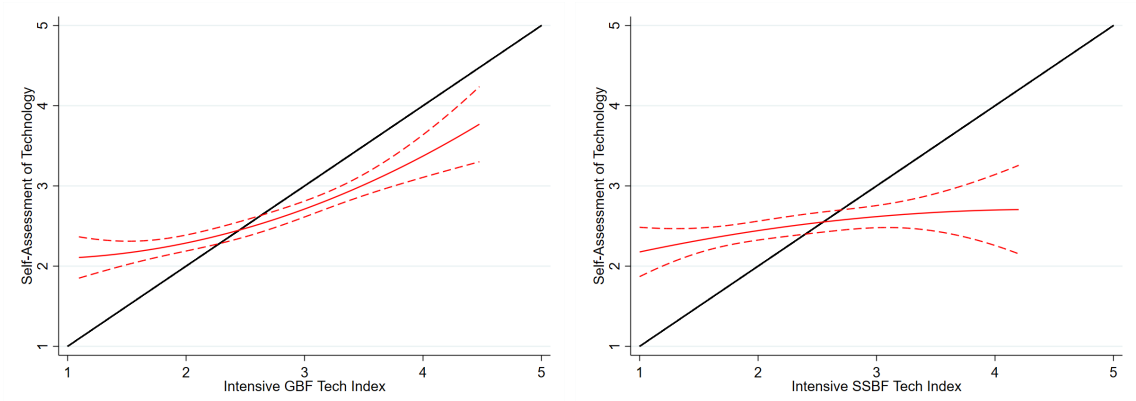


Indeed, most firms in Ceará are overconfident - they believe they are more advanced technologically than they actually are - regarding the level of adoption they have. If firms do not see the need for improving their technology, it is difficult that they are willing to adopt them. The FAT survey asks for a self-assessment of technology from 1 to 10 (here re-scaled to 1 to 5) before asking the technology adoption questions to prevent any bias in the self-assessment.[10] Figure 24 shows the scatter plot of firms' self-assessment with respect to other firms and the actual intensive index for both GBFs and SSBFs. Most firms with indices under 2.5 are placed above the 45 degrees line, thus indicating that they believe they use more sophisticated technology than they actually do. This overconfidence

[10]The question asks "In a scale from 1 to 10, where 10 means that the establishment is using the most advanced production processes available in its sector, where do you think this establishment stands with respect to other firms in the world?"

is larger on those firms at lower levels of technology use, which implies that those actually most in need of technology upgrading may be the ones that are more reluctant to upgrade.

Figure 24: Association Between Self-Assessment and Technology Adoption

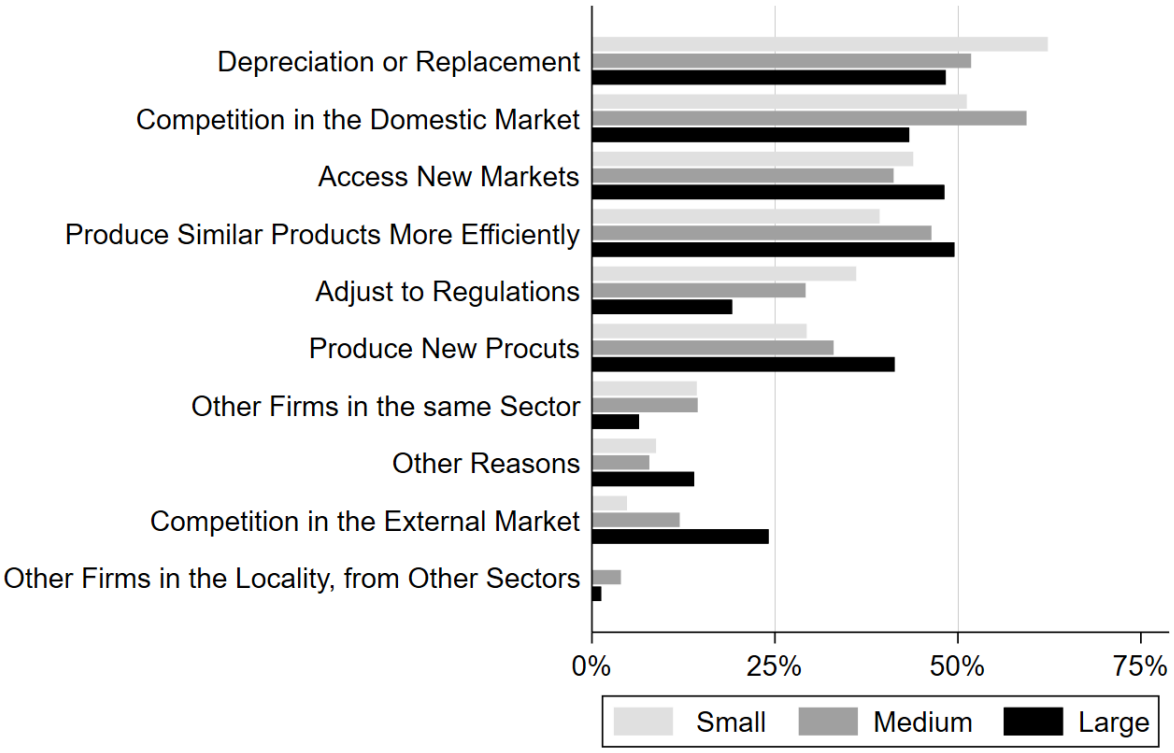


Note: Red line shows the quadratic fit with 95% confidence interval. Each technology measure is regressed on firms self-assessment with respect to the most advanced firms in the world, while controlling for sector, size, and regions.

6.4 Access to International Markets and Competition

Most firms adopt new technologies either due to depreciation or replacement or competition in the domestic market. The survey asks firms about their top three reasons to adopt technology. Figure 25 describes the share of firms reporting reasons to adopt by firm size group. The first motivation is depreciation or replacement, which is not an innovation motivation and can result in lack of upgrading in the use of technologies. The second motivation is consistent with the previous studies that competition may affect firm-level technologies (Milliou and Petrakis, 2011). 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.

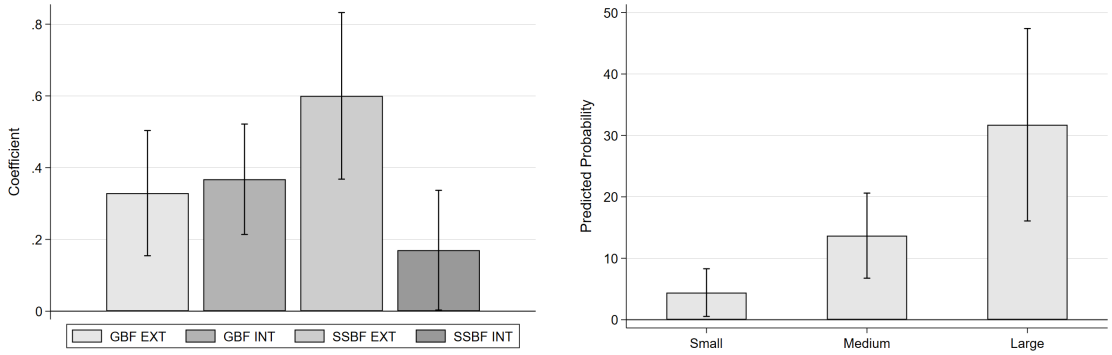
Figure 25: Main Reason to Adopt New Technologies



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

Trading is highly correlated with a higher technology index. Access to international markets have large effects to productivity via competition and learning, and these channels can also result in the use of more sophisticated technologies. Figure 26 panel (a) shows the relationship between trade status and the technology index. Traders (firms that export and/or import) tend to have between .17-.6 more sophisticated technologies than non-traders. This technology premium is less apparent for SSBF intensive margin. But large firms that are more likely to export and import, which is consistent with the behavior observed across firms around the world (Comin and Hobijn, 2004; Hobday, 1994; Rasiah and Gachino, 2005). While the probability of small firms to participate in trade is only 4.4% , up to 31% of large firms are exporting and/or importing. This implies that this international trade technology premium is concentrated mainly in larger firms.

Figure 26: Association Between Exporters/Importers and Technology Adoption



(a) Technology and trade

(b) Trade 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.

Figure 28 shows the technology indices of GBFs of exporting and non-exporting companies. Aside from payment methods, exporting companies use more advanced technologies for general business functions. In the intensive margin, the gap is particularly large for Production Planning, Marketing, and Business Administration.

Figure 27: Exporters

(a) Extensive margin

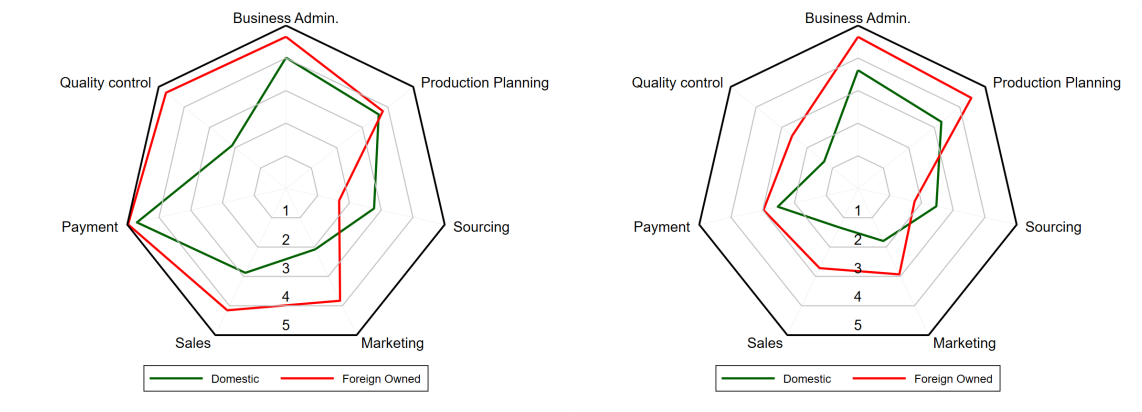
(b) Intensive margin

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

We also repeat the exercise of decomposing the technology index between domestic and foreign owned companies, those with more than 10% foreign ownership. In the extensive margin, domestic and foreign owned companies have similar indices for payment methods and production planning. Foreign owned companies show a larger index for quality control,

business administration, sales and marketing for both extensive and intensive margin, while sourcing and procurement is larger for domestic companies.

Figure 28: Domestic and Foreign Owned Companies



(a) Extensive margin

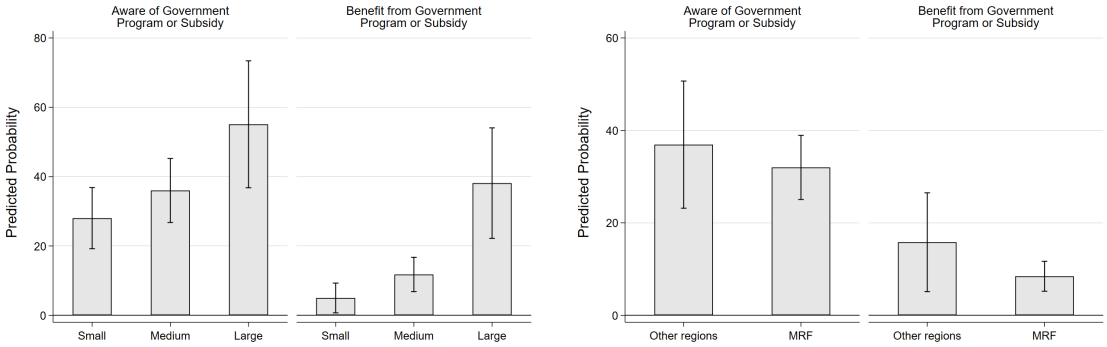
(b) Intensive margin

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

6.5 Access to government support

Small firms are less likely to be aware of government support programs to upgrade technology and only 5% are likely to benefit, despite the fact of having dedicated extension services for this segment of firms. Figure 29 shows that large firms have about 60% probability of being aware of government program or subsidy and almost 40% likely to benefit from these programs. The probabilities are much lower for small and medium firms. In terms of regions, firms outside the MRF have a higher probability of benefiting from government programs or subsidies, which is probably related to government's policies to reduce market concentration in the MRF and to attract large industries to the state. It is striking that despite the availability of a sistema S providing potential extension services to smaller firms, primarily, awareness and take up is still so small. More efforts on dissemination of programs to support technology extension are needed.

Figure 29: Awareness of Government Program and Subsidy



(a) Size (b) Region

Note: Panel (a) 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. Panel (b) presents the predicted percent of benefits from government program or subsidy by region 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

Firm capabilities are a critical driver of technology upgrading. 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 the size of the firms, sector, and region (see Table 6). Managers education is positively associated with technology adoption, both for the extensive and intensive margin and for general and sector specific business functions. There is also a positive association with the share of workers with college degree, managers' experience in large firms and firm's relationship with multinationals. We do not find significance, however, on the finance variable or the access to links to GVCs and distance or agglomeration with other firms. These results emphasize capabilities as a key driver of technology adoption.

Table 6: Technology Adoption Is Associated with Access to Knowledge and Information

VARIABLES	**GBF Ext**	**GBF Int**	**SBF Ext**	**SBF Int**
Loan for Machine	0.031	0.039	-0.008	-0.057
	(0.028)	(0.037)	(0.041)	(0.055)
Similar Products in 50km	0.037	0.042	0.036	0.026
	(0.029)	(0.038)	(0.054)	(0.051)
Supplier and Buyers in 50km	0.020	0.005	0.036	-0.041
	(0.041)	(0.050)	(0.066)	(0.060)
Supplier or Buyer MNCs	0.088***	0.086**	0.074	0.116*
	(0.031)	(0.040)	(0.061)	(0.063)
Manager Experience in Large Firms	0.017	0.002	0.088*	0.096**
	(0.027)	(0.035)	(0.046)	(0.048)
Use of External Consultant	0.049**	0.055	0.100*	0.015
	(0.025)	(0.034)	(0.055)	(0.053)
Benefit from Government Support	0.014	0.043	0.018	0.087
	(0.033)	(0.034)	(0.063)	(0.054)
Manager with University or More	0.078***	0.066*	0.148***	0.109**
	(0.029)	(0.038)	(0.055)	(0.049)
% of Worker with College	0.001	0.002**	0.003**	0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Log Total Employees 2018	0.071***	0.096***	0.065**	0.044
	(0.013)	(0.017)	(0.026)	(0.029)
Constant	0.561***	0.138*	0.632***	0.665***
	(0.070)	(0.075)	(0.088)	(0.095)
Observations	676	676	454	454
R-squared	0.355	0.372	0.364	0.300
Sector FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES

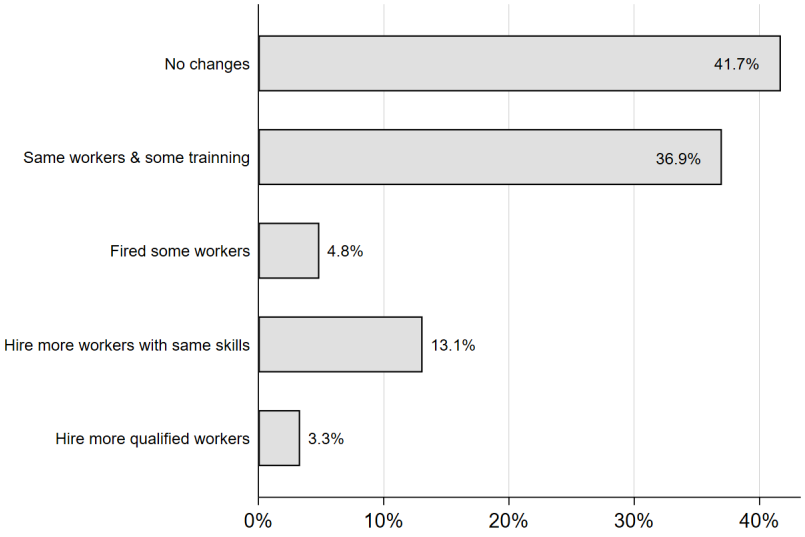
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

7 Technology and Employment

The relationship between technology adoption and employment has gained significant traction in the last decade with the emergence of advanced labor-saving technologies and the evidence in more advanced countries on job polarization (Autor et al., 2006; Acemoglu and Autor, 2011).

Most firms that adopt new technologies do not change their labor force when doing so. The survey asks about how firms adjust their labor composition to the adoption of new technologies through the acquisition of a new machine, equipment, or software. More than 78% of firms suggest that they do not change the number of workers, and about 37% suggest that they offer some additional training to current workers (Figure 30). Only a small number of firms, about 5%, report a reduction in the number of workers as a mechanism of adjustment for the acquisition of new technologies, which is a much smaller share than the number of firms that report an increase in the number of workers with same skills (13.1%) or hire more workers with more qualified skills (3.3%).

Figure 30: How Firms Self-Report Their Adjustments to New Technologies?



Firms with more sophisticated technologies also grow more. Table 7 shows a positive and statistically significant association between employment growth (between 2016 and 2018) and technology adoption and use, across different measures of technology and even after controlling for the initial size of the firm, their age, sector, region, foreign ownership, and exporting status. Although these results do not infer a causal relationship, they are in line with other findings in the literature suggesting that firms with better technologies tend to be more productive and benefit from opportunities to expand. The correlation between

firm growth and the level of technology is more robust for general business functions and higher for the intensive margin index.

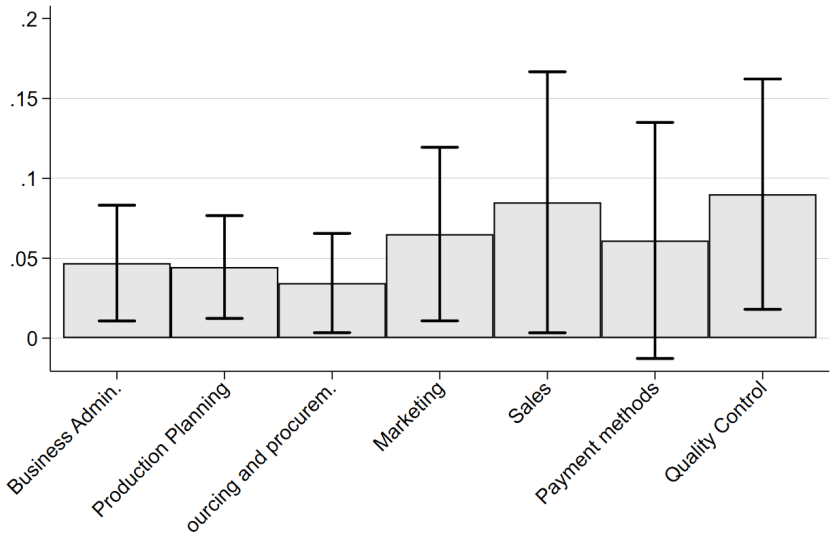
Table 7: Employment Growth and Tech Adoption (Extensive and Intensive Margins)

	(1)	(2)	(3)	(4)	(5)	(6)
ABF Ext	0.109*	0.121***				
	(0.066)	(0.041)				
GBF Ext			0.112***	0.120***		
			(0.043)	(0.032)		
SBF Ext					0.080*	0.071*
					(0.048)	(0.037)
Ln (Employment 2016)	-0.103***	-0.102***	-0.139***	-0.139***	-0.097***	-0.089***
	(0.033)	(0.029)	(0.026)	(0.026)	(0.034)	(0.029)
Observations	450	449	669	668	450	449
R-squared	0.064	0.215	0.115	0.242	0.057	0.198
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	0.155**	0.185***				
	(0.066)	(0.052)				
GBF Int			0.144***	0.160***		
			(0.047)	(0.039)		
SBF Int					0.091**	0.088*
					(0.046)	(0.047)
Ln (Employment 2016)	-0.104***	-0.105***	-0.143***	-0.147***	-0.089**	-0.082***
	(0.036)	(0.029)	(0.027)	(0.027)	(0.037)	(0.027)
Observations	450	449	669	668	450	449
R-squared	0.073	0.232	0.129	0.256	0.050	0.196
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.

Having more sophisticated technologies in sales, quality control and marketing are more correlated with larger employment growth. When analyzing the association between technology use and employment growth associated to specific general business functions, we observe a positive and statistically significant association for all functions in the intensive margin. Figure 31 shows that this coefficient is larger for sales, quality control and marketing.

Figure 31: General Business Functions and Job 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.

Finally, 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. One important question for the impact of technology on employment is how adoption of more sophisticated technologies affect the skill composition towards skilled workers; the skill bias technological change hypothesis. To investigate this relationship, we analyze the correlation between the technology index 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 8 shows a non-significant association between changes in the skill intensity and the level of technology, controlling for the initial size of the firm. [11]

[11] 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 8: Change in the Share of High-Skill Occupations and Tech Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
ABF Int	-0.009	-0.014				
	(0.019)	(0.014)				
GBF Int			-0.002	-0.014		
			(0.015)	(0.013)		
SBF Int					-0.019*	-0.010
					(0.011)	(0.011)
Ln(Employment 2016)	0.022*	0.016*	0.020**	0.019**	0.023*	0.015*
	(0.011)	(0.009)	(0.008)	(0.009)	(0.012)	(0.008)
Constant	-0.035	-0.168**	-0.051	-0.127***	-0.022	-0.171***
	(0.048)	(0.069)	(0.035)	(0.048)	(0.034)	(0.066)
Observations	450	449	669	668	450	449
R-squared	0.032	0.305	0.034	0.111	0.040	0.303
R-squared	0.006	0.032	0.008	0.016	0.005	0.031
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

The technology gap in Ceará, as expected, is significant and promoting technological upgrade of existing firms, specially SMEs, should be a key priority for the development of the state. This paper has provided a very granular view of technology adoption and use and documented the existing gap at various margins for firms with more than 5 workers.[12] Addressing the gaps and obstacles highlighted in the paper is critical to generate better firms and higher quality jobs. This can have a large impact on the economy and inclusion in Ceará.

These technology gaps are larger in smaller firms and in manufacturing, heterogeneous across business functions, and with significant gaps in Industry 3.0 and digitization, and especially large in Industry 4.0 technologies. The data collected showed that Ceará is still far from digitizing most business functions, and the use of Industry 4.0 technologies is incipient. We showed that technology gaps vary significantly across business functions. More importantly and despite policy makers' traditional focus on manufacturing, the technology gap is smaller in services and agriculture.

The analysis identified lack of firm capabilities as a key obstacle for technology adoption, and showed large room to improve existing support policies. Ceará

[12] According to Brazil's last firm census (Relação Anual de Informações Sociais) from 2018, formal firms with fewer than 5 employees account only to 7% of the workers in Ceará.

has relevant agencies within the "Sistema S" (for instance, SEBRAE and SENAI) conducting several programs to support businesses. Surprisingly, awareness of potential support, especially among smaller firms, is very low. More work is needed to provide information to firms on what technologies are available, support training on workers and management skills, and support technology upgrading.

The current COVID-19 pandemic is showing how urgent the technology upgrading agenda is to make business more flexible and prepared. The current pandemic has highlighted the need for digitization of businesses to respond to some of the lockdown restrictions and potential longer term demand effects. Online sales, integrated digital systems that support home-based work in some sectors, and automated production systems have become imperative during the crisis. However, firms in Ceará were not ready. The technological imperative is critical and that requires a more coordinated and granular support from the technology extension providers.

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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:

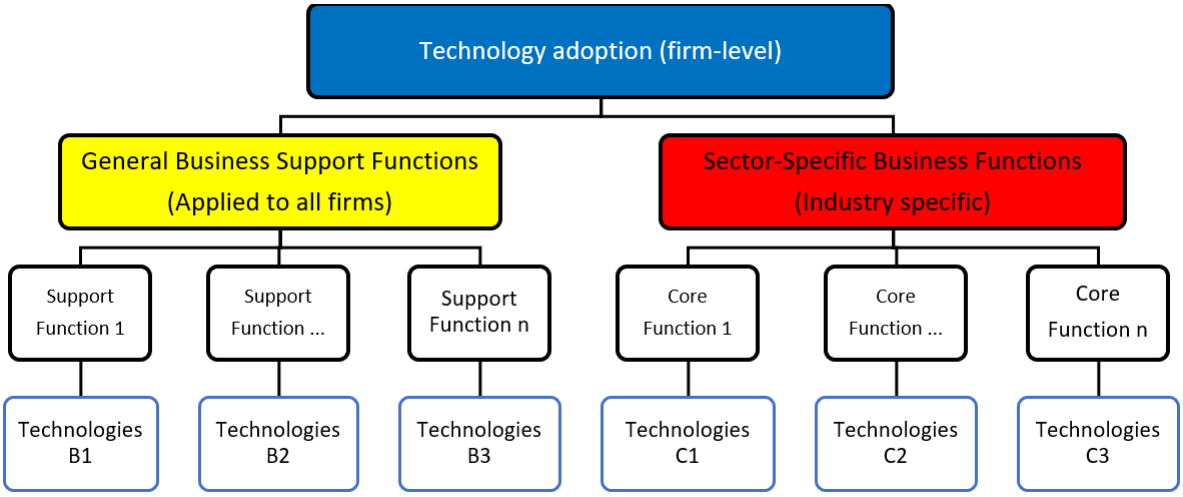
- Module A– Collects general information about the characteristics of the establishment.
- Module B – Covers the technologies used in eight generic business functions.
- Module C – Covers the use of technologies for functions that are specific to each of ten industry and services sectors
- Module D – 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 $R_f \leq N_f$.[13] 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

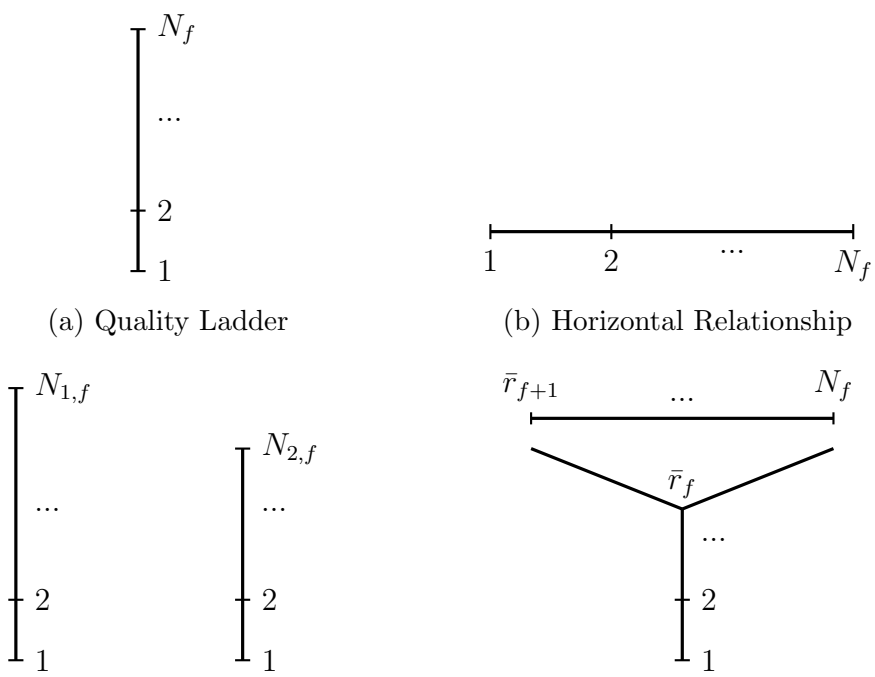
$$T_{f,j}^{INT} = 1 + 4 * \frac{r_{f,j}^{INT}}{R_f} \tag{1}$$

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.

[13] 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



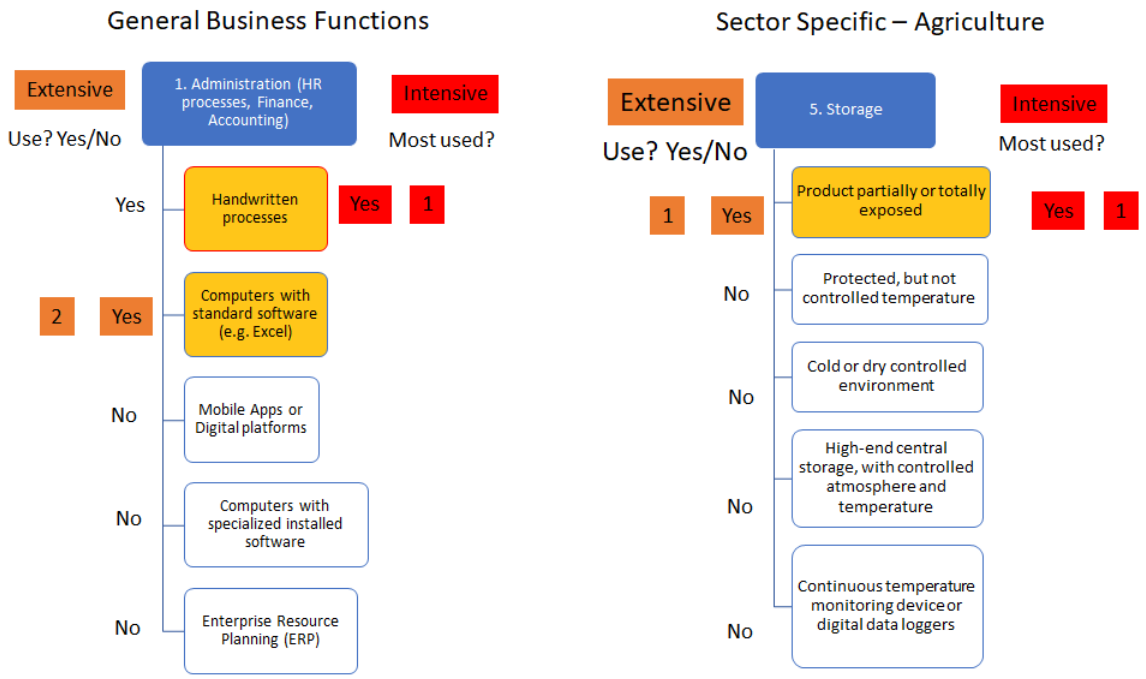
(a) Quality Ladder (b) Horizontal Relationship

(c) Hybrid I (d) Hybrid II (Tree)

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	-0.052	-0.105**	-0.192***	-0.333***
	(0.045)	(0.048)	(0.055)	(0.061)
Services	0.098**	0.118**	-0.263***	-0.424***
	(0.046)	(0.050)	(0.046)	(0.050)
Firm age (6-10)	-0.081*	-0.114*	-0.240**	-0.272***
	(0.047)	(0.066)	(0.113)	(0.080)
Firm age (11-15)	-0.039	-0.084	-0.236**	-0.181**
	(0.052)	(0.069)	(0.112)	(0.088)
Firm age (>15)	-0.000	0.001	-0.080	-0.066
	(0.041)	(0.051)	(0.088)	(0.057)
Multinationals	0.153***	0.214***	-0.011	-0.037
	(0.051)	(0.051)	(0.082)	(0.085)
Exporting	0.118***	0.157***	0.280***	0.042
	(0.025)	(0.033)	(0.101)	(0.052)
Region (MRF)	0.104***	0.133***	0.078	0.055
	(0.040)	(0.043)	(0.053)	(0.054)
Ln (Employment 2018)	0.093***	0.118***	0.108***	0.086***
	(0.013)	(0.016)	(0.022)	(0.022)
Constant	0.770***	0.373***	0.901***	0.824***
	(0.059)	(0.069)	(0.107)	(0.080)
Observations	699	699	472	472
R-squared	0.258	0.307	0.240	0.200

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	0.777**			
	(0.392)			
GBF Int		0.742**		
		(0.330)		
SBF Ext			0.583	
			(0.430)	
SBF Int				0.222
				(0.396)
Ln (Employment 2018)	-0.039	-0.054	-0.030	0.020
	(0.076)	(0.078)	(0.111)	(0.106)
Constant	8.171***	8.497***	8.269***	8.514***
	(0.367)	(0.287)	(0.479)	(0.447)
Observations	547	547	365	365
R-squared	0.125	0.129	0.141	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	0.407***	0.364***
	(0.090)	(0.082)
Large	1.041***	0.997***
	(0.090)	(0.077)
Manufacturing	-0.147	-0.196*
	(0.128)	(0.110)
Services	0.292**	0.295***
	(0.134)	(0.114)
MRF	0.331***	0.320***
	(0.110)	(0.091)
Constant	2.668***	1.855***
	(0.125)	(0.110)
Observations	711	711
R-squared	0.230	0.268

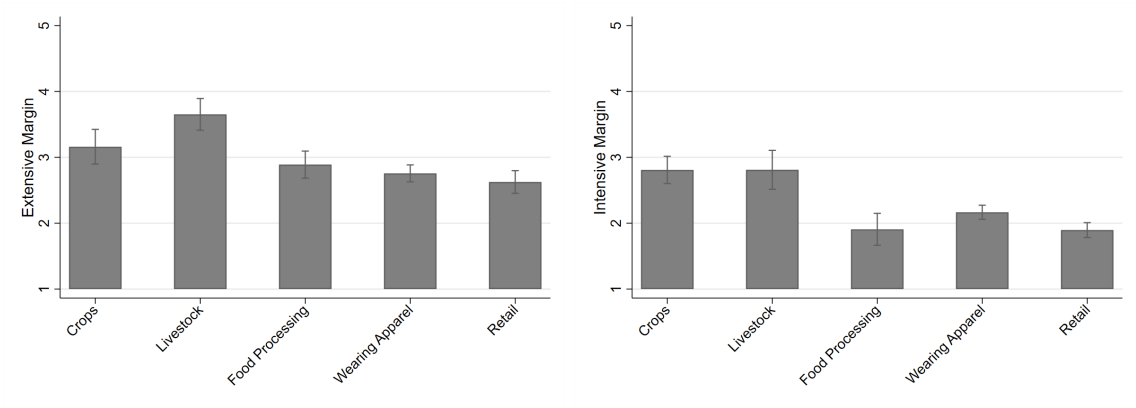
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

Table C4: Sector-Specific Business Functions Heterogeneity

VARIABLES	SSBF Ext	SSBF Int
Medium	0.307**	0.307**
	(0.147)	(0.147)
Large	0.948***	0.948***
	(0.153)	(0.153)
Livestock	0.491***	0.491***
	(0.154)	(0.154)
Food Processing	-0.271	-0.271
	(0.167)	(0.167)
Wearing Apparel	-0.405***	-0.405***
	(0.150)	(0.150)
Wholesale or retail	-0.536***	-0.536***
	(0.121)	(0.121)
MRF	0.253**	0.253**
	(0.126)	(0.126)
Constant	2.787***	2.787***
	(0.127)	(0.127)
Observations	448	448
R-squared	0.151	0.151

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.