Firm-level Technology Adoption in Malawi's Formal Sector

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Abstract

Technology adoption is key to boost productivity growth and poverty reduction in Malawi. This paper describes a novel approach to measure technology adoption at the firm level and applies to a sample of formal and non-agricultural firms in Malawi. It analysis the use and adoption of general purpose and sector-specific technologies in the country, identifying some of the key barriers to adoption and diffusion. The survey allows for establishing several new stylized facts. First, the adoption of general-purpose ICT technologies, such as smartphones, the Internet, and cloud computing for business purpose are low, but very heterogeneous and positively associated with size. Second, most firms still rely on pre-digital technologies to perform general business functions, such as business administration, production planning, supply chain management, marketing, sales, and payment. Third, most firms still utilize manual methods and face-to-face interactions to perform critical production tasks that are sector specific, such as packaging in food processing and credit approval in financial services. Lastly, we present evidence on the three main perceived obstacles for technology adoption: lack of demand and uncertainty, lack of capabilities, and access to finance.

1 Introduction

Despite Malawi's recent political stability, the country has struggled to grow at the same pace as other Sub-Saharan economies. The economy remains heavily dependent on the agricultural sector, which accounts for over 25% of GDP and 87% of the labor force, and concentrated on small and low-productive farmers. More recently, structural change out of agriculture has been limited to a few low-productive services sectors, mainly wholesale, retail, government services, and construction, thus limiting the productivity gains (World Bank, 2018, 2020). Moreover, given the high costs associated with its geographical position - landlocked -, Malawi faces many competitive disadvantages in trade and has not developed a broader export base. The top five products - unmanufactured tobacco, raw sugarcane, gold, tea, and dried legumes – account for 89% of goods exports.

To raise income and ultimately reduce poverty, now estimated to affect 70% of the country's population, Malawi will have to overcome low productivity growth rates and diversify the economy. In the agricultural sector, productivity has been mostly stagnant, with most of the sector's growth deriving from increased land under cultivation and labor (World Bank, 2018, 2020). The country's heavy dependence on the sector has also made it more susceptible to external shocks, especially climatic shocks. Diversification and productivity growth will also be crucial in the context of the Covid-19 pandemic, which threatens to increase informality and the number of people living in extreme poverty in the country.

A critical response to address these challenges is technology upgrading. Adopting and using more sophisticated technologies can accelerate productivity growth and reduce the country's technology gap with developed economies (Comin and Hobijn, 2010; Comin and Mestieri, 2018a; Easterly and Levine, 2001; Hall and Jones, 1999). Designing innovation and technology policies will require understanding the key barriers preventing Malawi firms from adopting more advanced technologies, which in turn involves adequate measures in technology use at the firm level. Access to this information is usually confined to a few technologies and sectors, and the lack of available data is exceptionally large in developing countries, making it challenging to examine whether firms in Malawi use better technologies that already exist and why. Therefore, a deeper understanding of the meaning of new technologies, their use, and the obstacles to adoption requires appropriate tools and methodologies to measure their diffusion.

This paper describes the "Firm-level Adoption of Technology" (FAT) survey implemented in Malawi. It identifies some of the key obstacles to the adoption of new technologies faced by those firms. The paper describes the level of technology use across firms and sectors with large granularity and provides some benchmarks and relationships between technology use and performance. The FAT survey developed by Cirera et al. (2020) is an innovative tool to measure the use of technology at a granular level. The study implemented in Malawi includes a nationally representative random sample of 465 formal firms with five or more employees in non-agricultural sectors from the latest Malawi establishment census.

In the paper, we analyze the adoption and use of technologies in Malawi through three key angles: (1) standard measures of technology related to general-purpose technologies; (2) use of technologies applied to general business support functions; and (3) use of sector-specific technologies. The standard firm-level measures of technologies refer to "traditional" measures of general-purpose technology (GPT) adoption, enabling firms to apply more technologies in non-specific tasks. It includes the access and usage of GPTs such as electricity, phone, computers, the internet, cloud computer, and digital platforms. We define general business support functions (GBF) as those tasks necessary in any firm, regardless of the sectors they are in, such as business administration, production planning, sales or payment methods. The sector-specific business functions (SSBF) are applied for industry-specific business functions (e.g., land preparation in agriculture industries or input testing in the food processing industry) and often refer to sector-specific production processes.

For each general and sector-specific business function, we measure the most frequently technologies used (*intensive margin*). The distinction between these margins provides a very granular measure of technology adoption to inform policy decisions. For example, when asked about adopting a particular technology such as digital payment methods, many firms may report that they are already using it (*extensive margin*). Still, very few of them may be using this technology intensively (*intensive margin*). By disentangling the differences between the extensive and intensive margins, we can have more clarity to inform policy, such as if lack of adoption is a problem of infrastructure or if this is more related to lack of firms' capabilities. To our knowledge, this is the first study providing a comprehensive analysis of technology adoption at the firm-level using a standard methodology across different sectors and based on representative data for the formal sector in Malawi.[1]

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 the Internet, without identifying the specific purpose of use. Section 3 describes the new measures of technologies developed using the FAT survey and provides a conceptual framework for general and sector-specific business functions. Section 4 analyzes the level of technology adoption and use for general business functions. Section 5 explores the level of technology adoption and use for sector-specific technologies. Section 6 describes some of the key barriers

[1]The coverage of technology questions in standard firm-level data sets is almost negligible, even for high-income economies.

and drivers to technology adoption and use. Section 7 analyzes the relationship between technology use and employment. The last section concludes.

2 Standard measures of technologies: Electricity, ICT, and Industry 4.0

This section describes the adoption of general-purpose technologies (GPTs), classified according to different stages in which these technologies became available. Specifically, we divide the information into three broad industrial phases: Industry 2.0, 3.0, and 4.0. Industry 2.0 encompasses electricity and generators, which are technologies from the 1880s, while industry 3.0 refers to the ICT revolution, including mobile phones, computers, and the Internet.[2] Industry 4.0 refers to technologies with some digital components and a higher level of autonomy and information exchange across different devices and machines. 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.[3]

2.1 Industry 2.0: Electricity

97% of formal firms in Malawi face constant power outages and 62.6% have a generator. Table 1 shows the descriptive statistics of access to electricity, power outages, and alternative electricity sources by size group. The first two columns show the average and standard deviation. Three firm size groups are defined by the number of employees: small (5-19), medium (20-99), and large (100+). Given the focus on non-agricultural and formal firms, access to electricity is extensively available in the country.[4] Access is more extensive for medium and large companies; about 7% of small firms don't have access to electricity. Given the frequency of power outages, 62.6% of firms have their generator, with 91.6% relying on fuel as the primary energy source. Although a large share of medium and large firms uses generators, very few use alternative energy sources such as solar or wind-power; only 3.2% of the generators use solar power as the primary energy source.

[2] Comin and Mestieri (2018b) presents the reference year of invention for these technologies: electricity (1882), PCs (1973), Cellphones (1973), and Internet (1983).

[3] Nayyar and Hallward-Driemeier (2018) provide further discussions on the emergency of Industry 4.0. Although some of these technologies, such as AI, were already available since the 1960s, diffusion has gained momentum only recently.

[4] In fact, in 2018 Malawi was one of the least electrified countries in the world, with only 18% of the population having access to electricity.

Table 1: Industry 2.0: Access and quality of electricity (percentage)

Technology	Mean	SD	Small	Medium	Large
Having Electricity	96.4%	0.19	93.3%	100.0%	99.2%
Power Outage	97.0%	0.17	97.2%	100.0%	92.1%
Having Generator	62.6%	0.48	43.0%	76.2%	94.6%
Energy: Solar Power	3.2%	0.18	3.3%	0.0%	7.1%
Energy: Fuel	91.6%	0.28	85.7%	97.9%	91.2%
Energy: Wind Power	0%	0.00	0%	0%	0%

2.2 Industry 3.0: ICT

While many firms have access to mobile phones, other basic technologies, such as smartphones and the internet, are not widely available. Table 2 shows the summary statistics on general-purpose technologies, evidencing a clear and positive correlation between access to basic technologies and firms' size. For instance, 100% of large firms have a computer, against only 70% in the case of small firms. The divergence in the adoption of computers and smartphones or tablets for business purposes is more evident when considering the intensive margin. On average, small firms have about two computers per firm, while medium firms have about 9.5 computers per firm, and large firms have over 30 computers, either desktop or laptop, per firm. There is also a clear correlation between firms' size and internet access. While only 60.6% of small firms have internet access, we see almost universal access for large firms. The difference is also evident in terms of the quality of internet access. 23.4% of small firms still rely on dial-up internet, against only 1.7% in the case of large firms. However, large firms are more susceptible to internet disruption (on average, 11 times in a typical month) than small and medium size firms (2.9 and 3.3 times, respectively).

Table 2: Access to ICT

Technology	Mean	Std. Dev.	Small	Medium	Large
Having Telephone	59.6%	0.49	45.8%	65.6%	88.0%
Having Mobile Phone	91.5%	0.28	89.8%	89.9%	98.7%
Having Computer	82.1%	0.38	70.0%	91.8%	100.0%
Having Smartphone	51.0%	0.50	50.4%	56.1%	44.5%
Having Internet	72.5%	0.45	60.6%	77.2%	97.8%
Type: Dial Up Internet	14.2%	0.35	23.4%	11.9%	1.7%
Type: DSL Internet	17.7%	0.38	12.2%	18.4%	25.8%
Type: Wireless Internet	66.0%	0.47	60.0%	69.4%	71.9%
Type: BPL Internet	0.1%	0.04	0.0%	0.0%	0.6%
Internet disruption	5.5	9.0	2.9	3.3	11.0
Number of Telephones	2.8	12.3	1.0	2.6	8.0
Number of Mobile Phones	6.2	14.5	2.7	5.0	17.4
Number of Computer	9.8	32.8	2.3	9.5	30.9
Number of Smartphone	2.9	11.6	1.5	2.7	7.0

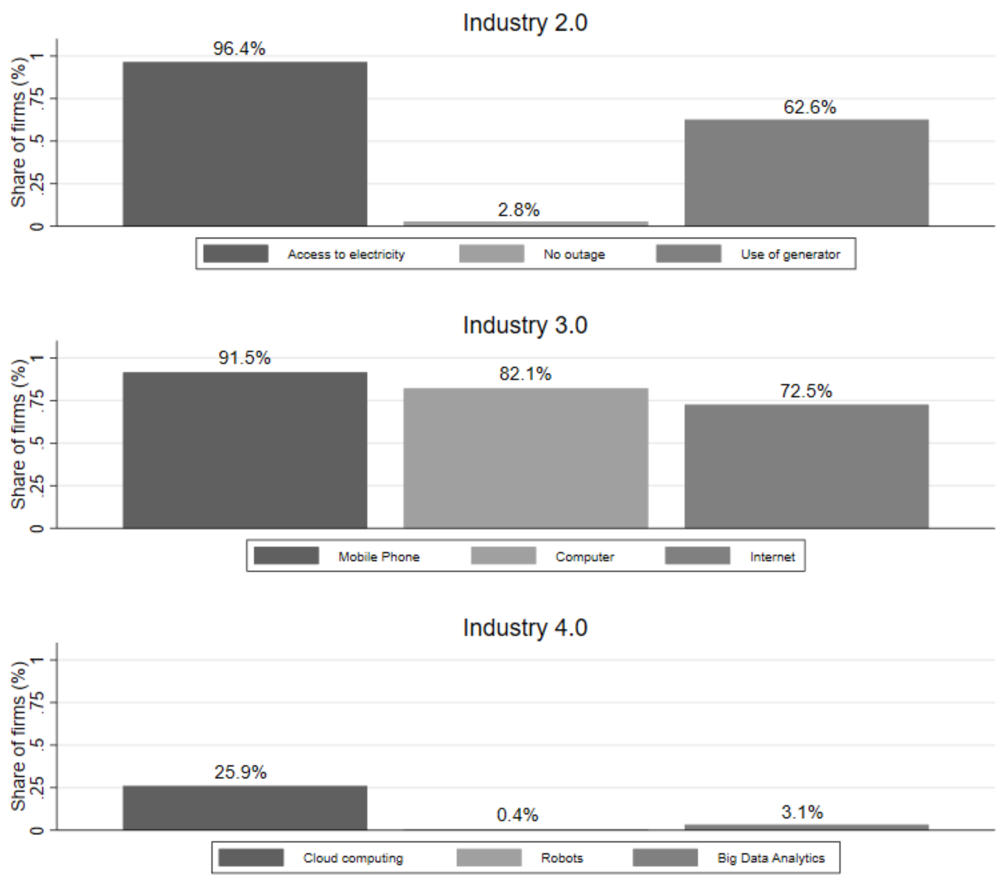
2.3 Industry 4.0

Few firms in Malawi have adopted industry 4.0 technologies.[5] Figure 1 shows the share of firms that have adopted the different technologies. For Industry 2.0 technologies, although access to electricity is almost universal in Malawi, access' quality remains poor; only 2.8% of firms have not faced constant power outages in the period. As a straightforward consequence of the significant infrastructural bottleneck, 62.6% of firms have their own generator. For Industry 3.0 technologies, 91.5% use mobile phones, while 82.1% use computers and 72.5% have internet access. Lastly, for Industry 4.0 technologies, the most frequently adopted technology is cloud computing, with over 25% of firms. However, in other more advanced technologies, particularly robots, adoption is close to zero.

Despite the novelty of some of the measures described in this section, a significant limitation is that we do not identify the purpose for which these technologies are being used. For example, we do not know the tasks for which computers or the Internet are used or how these technologies are being used in production. To address this issue, the next section explores and measures the purpose for which technologies adopted by firms are used.

[5]Industry 4.0 is characterized by new technologies such as robotics and artificial intelligence (AI) with high autonomy.

Figure 1: Summary of General Purpose Technology Adoption in Senegal

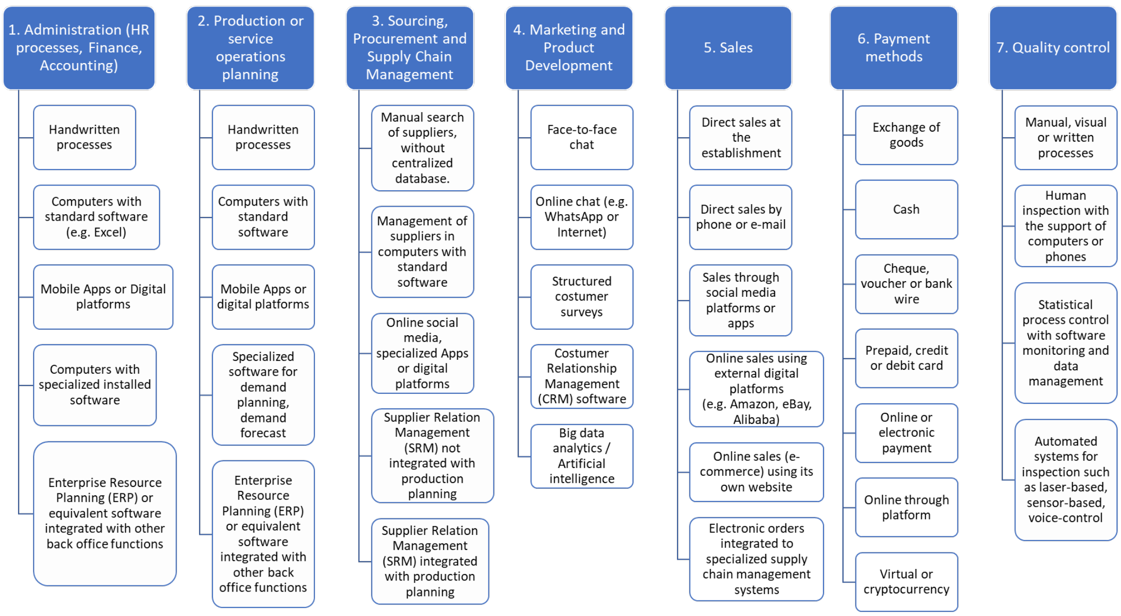


3 New Measures of Technology Adoption and Use: Linking Technologies to Business Functions

To identify the purpose for which a given 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 into 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 varies 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 2 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 2: 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 sector. The FAT survey in Senegal 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 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 a technology index based on the most frequently used technology to perform a business functions (intensive margin). The intensive margin is based on the most used technology to perform this task.[6]

Table 3 compares the different technology indices for Malawi, the State of Ceará in Brazil, Vietnam, and Senegal, with some important differences in the samples.[7] For instance, Malawi is the only country that does not include the agricultural sector in its estimates, whereas Senegal is the only country with information on the informal sector. Moreover, 22% of Malawian firms in our sample have at least 10% of private foreign ownership, compared to 13%, 6%, and 1.5% in Vietnam, Senegal, and Brazil, respectively. As a result, estimates for Malawi are likely to overestimate the use of advanced technologies, as formal and foreign firms are commonly more technologically advanced. However, even taking these caveats into account, Table 3 suggests that Malawi firms are far below the technological frontier.[8] For GPFs and SBFs, Malawian firms are only ahead of Senegal's firms but behind Senegal's formal companies. When compared to Ceará, which presents the highest indices in our sample, Malawi's gap varies from 0.85 (GBFs) to 0.41 (SBFs).

[6]For example, if the 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 method 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 Malawi, only the state of Ceará in Brazil, Senegal and Vietnam have been completed. Bangladesh is also completed but only includes some manufacturing sectors. Jamaica and the Philippines are on the field, and 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
	Intensive	Intensive
Average	1.78	1.60
Ceará (Brazil)	2.49	1.92
Vietnam	1.92	1.80
Senegal (formal)	1.69	1.56
Malawi	1.64	1.51
Senegal (informal)	1.18	1.21
Gap: Malawi - Ceará (Brazil)	-0.85	-0.41
Relative Gap**	21%	10%

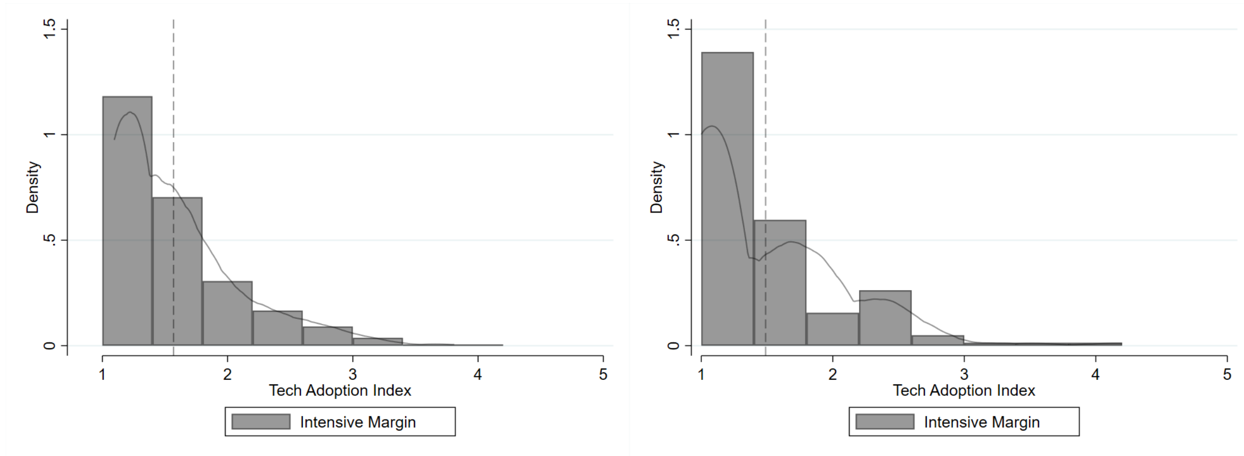
Note: Average is the average of Brazil, Vietnam, Senegal, and Malawi. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 ((Malawi - Ceará)/Maximum Gap(4)). Technology measures are weighted by the sampling weights.

Figure 3 presents the technology index distribution for GBFs and SSBFs across firms in Malawi. The highly right-skewed distribution shows that only a few firms adopt more advanced technologies and that most firms rely on the most basic technologies (values 1 and 2) to perform either GBFs or SSBFs. Meanwhile, the small share of firms adopting more advanced technologies is largely benefiting from it. Figure 4 shows that the use of more sophisticated technologies is correlated with an increase in value-added per worker, especially in the case of GBFs.[9] Although further investigation is needed to determine the causal relationship between technology adoption and performance, available evidence suggests that adopting technology pays off. Easterly and Levine (2001) and Comin and Hobijn (2010) and Comin and Mestieri (2018a) show that technology is a key driver of productivity differences across countries. Kwon and Stoneman (1995) show this relationship for firms in the manufacture and an extensive literature in agriculture has shown the impact of technology adoption on farms' productivity.

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

[9]The elasticity of the technology index with respect to value-added per worker is 1.1 for the intensive margin GBFs and 1 for the intensive margin SSBFs. Table C2 in the appendix provides the full results for these estimates.

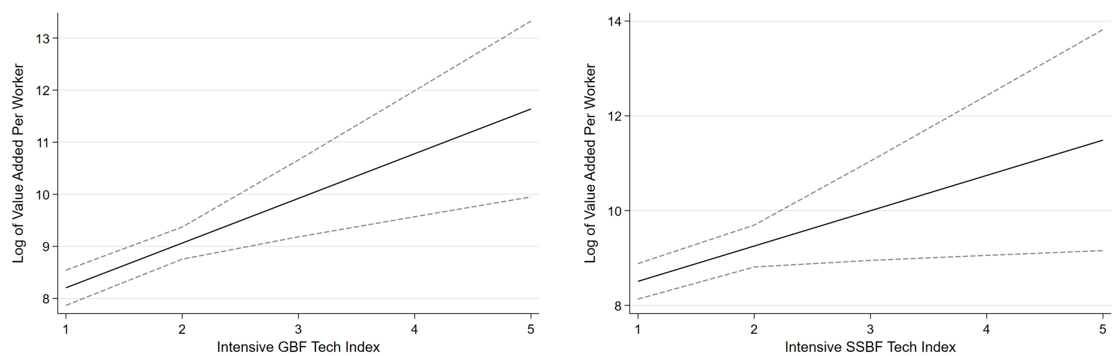
Figure 3: Technology Adoption – Firm-level Distribution



(a) General Business Function (b) Sector-Specific Business Function

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

Figure 4: Firm-level Tech Adoption Index and value added per worker



(a) Intensive GBF Tech Index (b) Intensive SSBF Tech Index

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 suitable comparator across firms, sectors, and countries.

4.1 The relationship between technology use and firm size

Across different size groups, firms in Malawi are far from the technological frontier. Figure 5 shows the average technology indices for the intensive margin by firm size. The solid and dashed horizontal lines indicate the average and median index for the country, respectively.

The GBF index varies from 1.4 to 2.1 in the intensive margin, suggesting a clear and positive correlation between firms' size and the adoption of more advanced technologies. Small firms in Malawi are mainly using the most basic technology available for general business functions. However, even for large firms, the technology gap to the frontier is significant.

Figure 5: GBFs: Intensive Margin in Malawi by Group Size

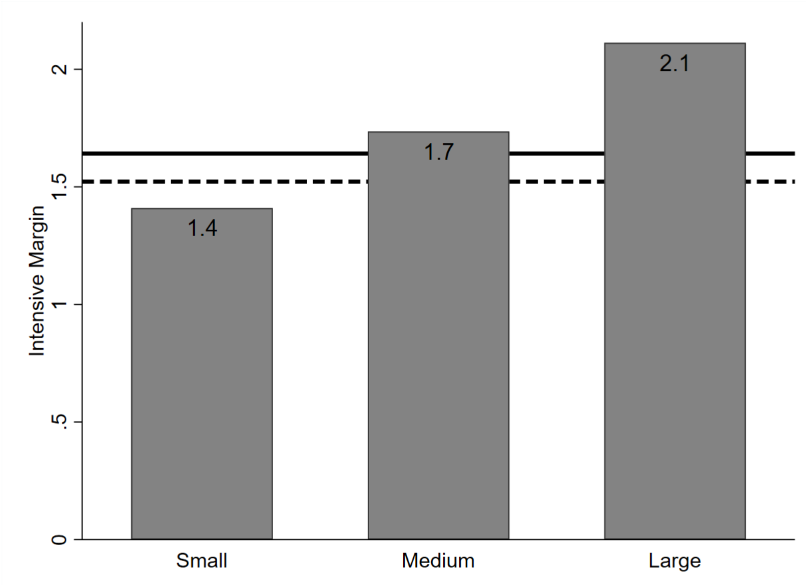


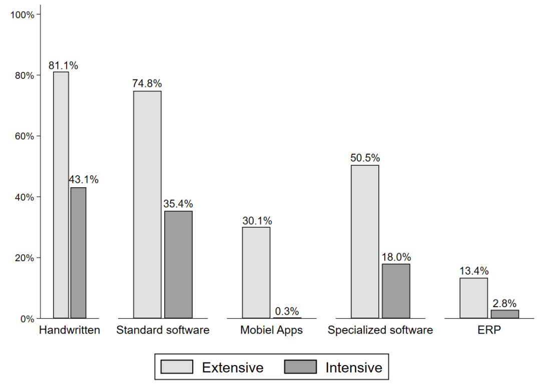
Figure 6 shows the average indices on the intensive margin for different general business functions, showing similar results across all general business functions. In fact, except for payment and business administration methods, intensive margin indices are all below two. Among different GBFs, large firms use more advanced business administration and production planning methods than small and medium-sized firms. The large gap between Malawian indices and the frontier clearly shows that most firms use simpler technologies, mainly relying on handwritten and manual processes.

Figure 6: General Business Functions in Malawi: Intensive GBF by size group

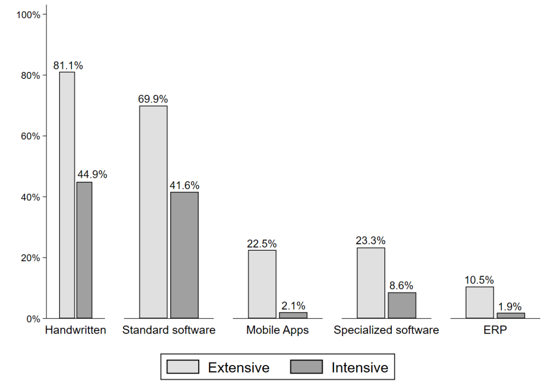
Note: Each line represents the index average across firms for each business function.

Figure 7 provides the level of adoption on the general business functions' intensive margins. The results suggest that most Malawi firms rely on handwritten processes and standard software for business administration and production operations. In the intensive margin, about 78% of firms use either of these methods for business administration, with only 18% using specialized software and 2.8% using ERP. Moreover, although 41.7% of firms use social media for sales, only 0.7% have stated that this is the most used technology. About 96% of companies sell their products either at the establishment or by phone or email; the more basic technologies. In the case of customer information, over 80% of firms in Malawi rely on face-to-face chat as their primary source of information. The results point out that even though some firms are adopting more sophisticated technologies in a given business function (e.g., payment methods), these are not the most used technologies.

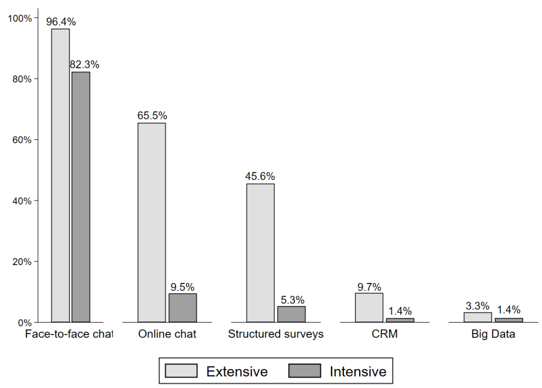
Figure 7: Share of firms using technologies applied to General business functions



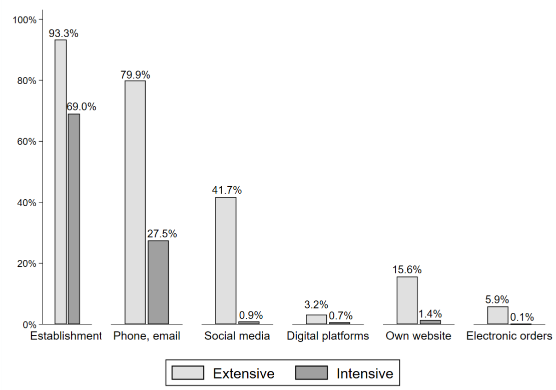
(a) Business administration processes related to account, finance, and HR



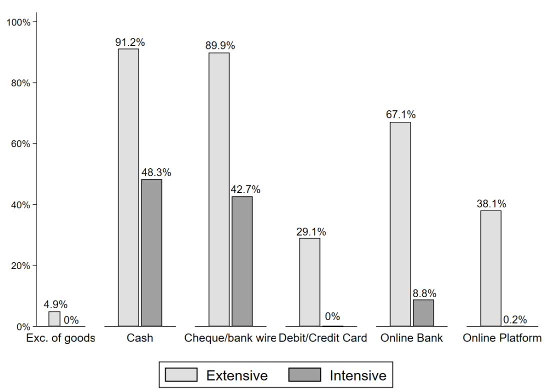
(b) Production or service operations planning



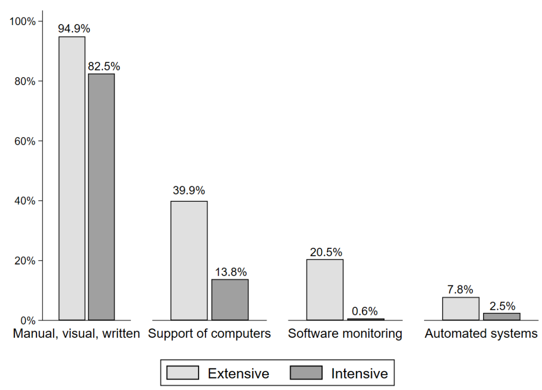
(c) Customer information for marketing and product development



(d) Sales Methods



(e) Payment Methods

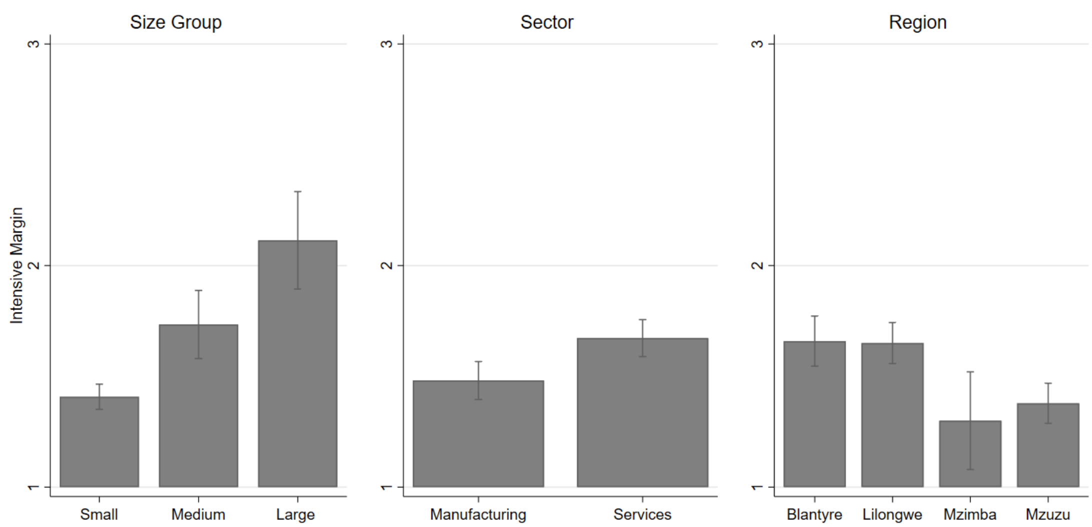


(f) Quality control inspection

4.2 Heterogeneity across size, region, and sector

Besides size heterogeneity, firms in Malawi also differ according to their region and sector. Figure 8 shows the heterogeneity of Malawi's technological adoption index by size, sector, and region. The figure shows significant regional heterogeneity, suggesting that firms in Blantyre and Lilongwe adopt more advanced technologies. Moreover, large firms and those in the services sector have the highest adoption index.

Figure 8: General Business Functions in Malawi - Heterogeneity



5 Sector Specific Business Functions

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

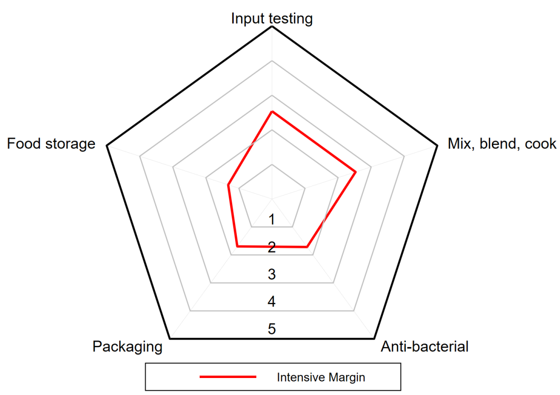
5.1 Manufacturing

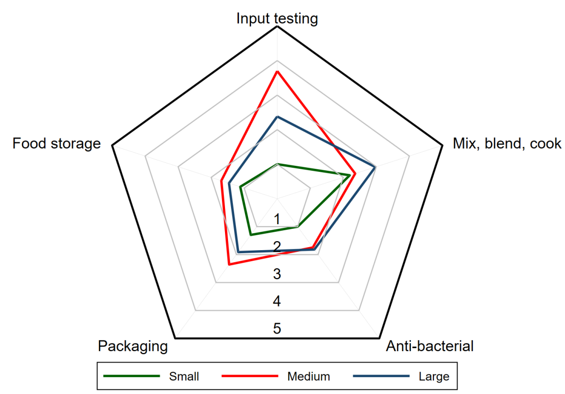
The index varies between 1.3 for food storage and 2.5 for input testing in the intensive margin in the food processing sector.[10] Overall, most SSBFs are performed with the use of obsolete technologies. For instance, only a small share of firms (38%) have mentioned utilizing "non-computer controlled testing kits" as the most used technology for input testing. The use

[10]The sample includes 34 firms, of which 18 are large companies.

of machines is also very incipient. Approximately 70% of firms use machines requiring human force for food preparation, and 60% rely on manual packing. Food storage also is carried mainly in minimal protection conditions (83%), with only 1.5% of firms using "fully automated climate and security-controlled buildings". Finally, in the case of anti-bacterial processes, the most used technique for almost 95% of the firms is either "minimal-processing preservation methods" or "anti-bacterial wash or soaking", the two simplest methods. The remaining 5% intensively use "thermal processing technologies". The figure also shows some significant differences among size groups. On the one hand, large firms use significantly more advanced technologies for input testing, food storage, and packaging. However, anti-bacterial methods are very similar across groups, whereas medium-sized companies apply more sophisticated methods for mix, blend, and cook.

Figure 9: Manufacturing: Food Processing





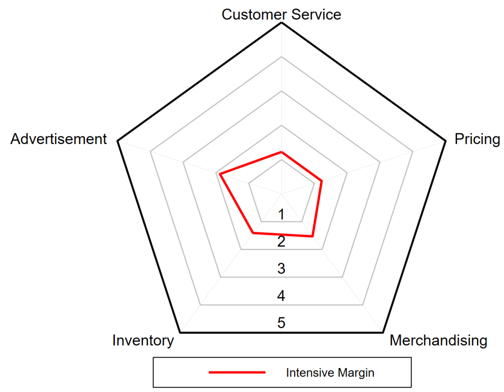
5.2 Services

On average, retail firms are still relying primarily on manual technologies for customer services, pricing, merchandising, inventory, and advertisement.[11] Fewer than 2% of them use social media for customer services as the most frequently used technology, with the majority of firms providing the services at the premise (83.5%) or by phone (12.4%). More than two-thirds of firms rely on manual cost for pricing strategy, while only 1.2% use "automated promotional". Similarly, 65% use "handwritten record" as the primary inventory method and 46% use paper-based communication as the primary advertisement channel. Finally, the use of either e-mail or mobile phones and social media respond for only 21% of the most frequently used technologies for advertisement. Differences between medium and small-size

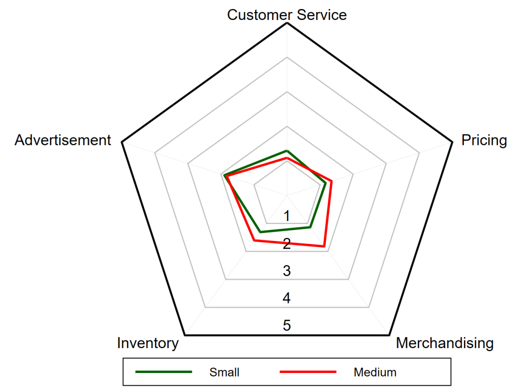
[11]The sample includes 124 small-size firms, 14 medium-size firms, and only one large firm, which has not reported information on the intensive use of SSBFs.

companies are relatively small, except for merchandising functions, in which medium-size companies are using more sophisticated technologies.

Figure 10: Services: Retail and Wholesale



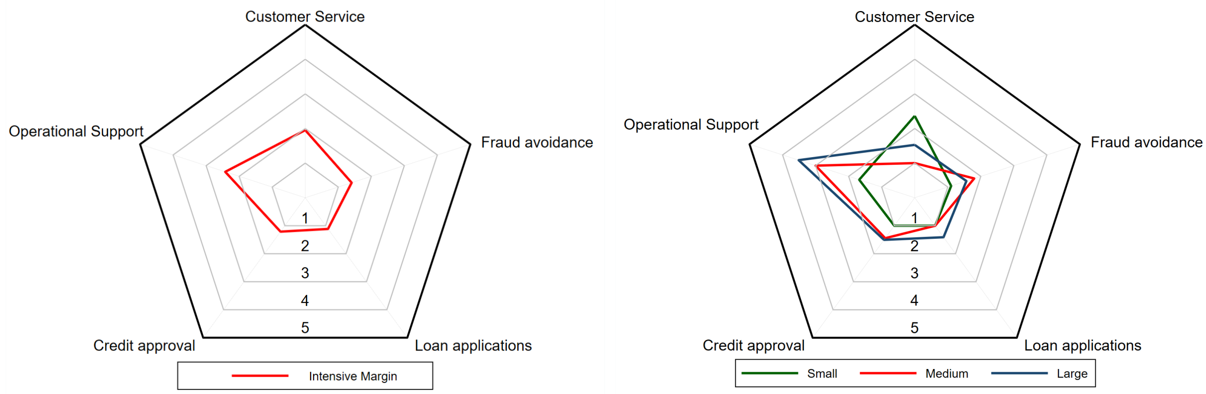
(a) Retail and Wholesale - SSBF



(b) Financial Services - SSBF

Similarly, the financial services sector has not broadly adopted digital technologies for its business functions. The sector still utilizes paper-based technologies and handles most of the processes at the premises. For instance, 65% of firms rely on face-to-face services for customer services related to checking and saving accounts, with no firm declaring mobile applications as the most used method. Fraud avoidance and customer identification are carried primarily with the use of "face-to-face with documentation", with less than 2% of firms using digital authentication services provided by other specialized companies. Moreover, loan applications occur mainly on the establishment, with no firm using internet or mobile applications as the primary technology. Digital technologies are more present in operational support functions, for which 18% use "centralized systems across branches". Operational support is especially more sophisticated for large firms, whereas small firms provide more advanced customer service technologies.

Figure 11: Services: Financial Services

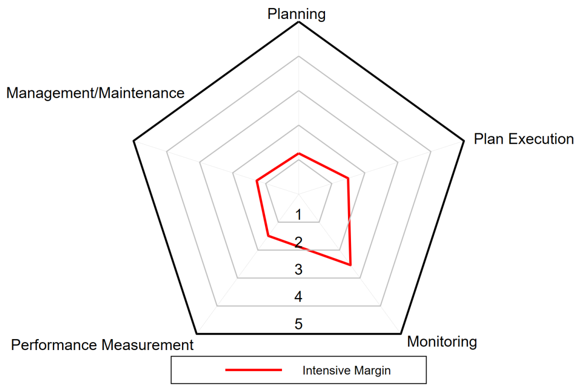


(a) Retail and Wholesale - SSBF

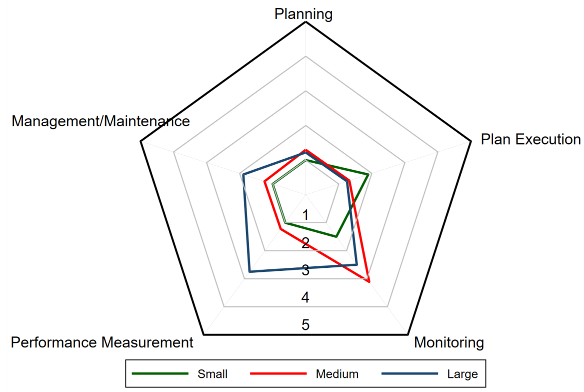
(b) Financial Services - SSBF

Land transport services present similar results to retail and wholesale, and financial services. Except for monitoring, the indices in all other sector-specific business functions are below 2, suggesting the intensive use of manual technologies. For transportation planning, 86% of firms utilize information collected by non-specialized workers to create their load plans, with the remaining 14% using data collected by email or FAX share. Similarly, plan execution is mainly carried with the use of "manual process with the support of fax, text, or phone calls" (73.8%). Less than 10% of firms use specific software such as GPS, dynamic routing, or others. In contrast, digital technologies are more present in monitoring functions, in which over one-third of Malawian firms intensively use specific software such as GPS, dynamic routing, or others. Finally, 71% use manually monitored and reported performance measurement processes, and almost 80% make use of paper-driven systems to carry fleet management and maintenance. Larger firms are intensively using more advanced methods for management/maintenance and performance measurement. In contrast, even though small firms are adopting mainly basic technologies, they also present a higher index for plan execution than medium and large-size companies.

Figure 12: Services: Land Transport



(a) Retail and Wholesale - SSBF

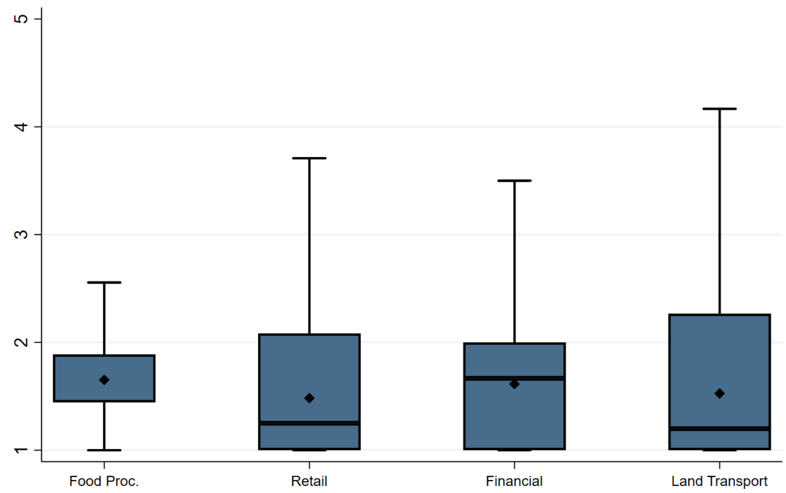


(b) Financial Services - SSBF

5.3 Cross-sector differences in sector-specific technologies

Comparing across sectors, on average financial services 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 13 shows the differences within and between sectors in SSBFs, and show some important facts about technology adoption in the country. First, it suggests that on average the financial services sector is using the most advanced sector specific technologies in Malawi, although the variance is large. Second, the within sector variance is larger for land transport. Interestingly, the variance within the Food Processing sector is small, indicating very similar technologies across companies.

Figure 13: SSBF - Sector Comparison

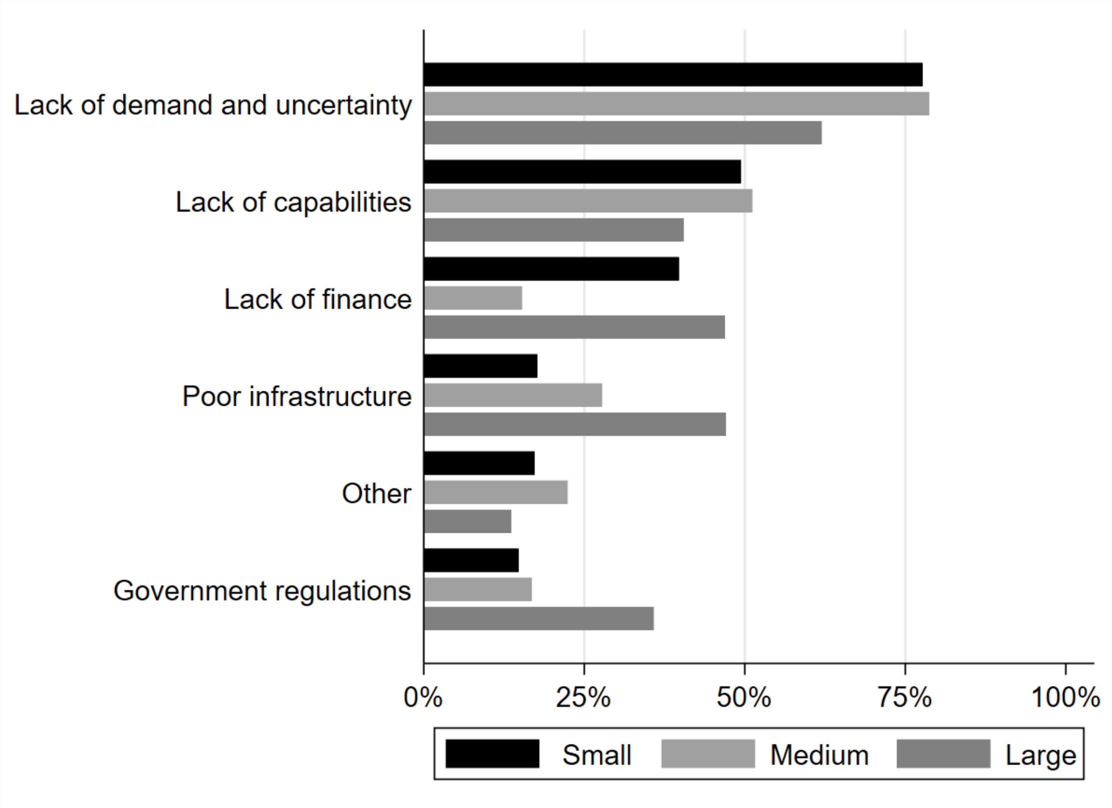


6 Barriers to technology adoption

6.1 Perceived barriers to adoption

The survey asks managers to identify the three more significant 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 14 describes the share of firms reporting main obstacles by size group. Lack of demand and uncertainty and lack of capabilities are the main perceived obstacles in Malawi. About 75% of small and medium firms have identified lack of demand and uncertainty as one of the three most significant barriers. Lack of demand and uncertainty refers to uncertainty about the returns to investing in technologies and whether their demand justifies such investments. Lack of capabilities refers to lack of information on what technologies are available and the lack of skills to use the technology. Overall, there is little variance across small and medium-sized firms, suggesting that these firms face the same types of obstacles. In contrast, large firms perceive lack of finance and poor infrastructure as more relevant barriers.

Figure 14: Perceived Obstacles for Adopting Technology by Firm's Size



We estimate a linear regression model to formally analyze 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 4). Firms' size is strongly and positively associated with technology adoption. Interestingly, none of the barriers is negatively and significantly associated with adoption. There is a positive and significant correlation between poor infrastructure and both indexes. The table also shows a positive relationship between other barriers and the GBF index at the intensive margin. Overall, the unexplained part of the technology index is large, likely related to the often low quality of these perceived obstacles.

Table 4: Technology adoption is associated with access to knowledge and information

VARIABLES	GBF Int	SBF Int
Lack of capabilities	0.055	-0.029
	(0.039)	(0.046)
Government regulations	0.056	0.041
	(0.046)	(0.054)
Lack of finance	-0.008	0.009
	(0.039)	(0.044)
Lack of demand and uncertainty	0.016	0.075
	(0.037)	(0.054)
Poor infrastructure	0.111**	0.097**
	(0.043)	(0.049)
Other	0.167***	0.019
	(0.050)	(0.070)
Ln (Employment 2018)	0.099***	0.120***
	(0.013)	(0.014)
Constant	-0.072	-0.045
	(0.072)	(0.105)
Observations	450	337
R-squared	0.450	0.423
Sector FE	YES	YES
Region FE	YES	YES

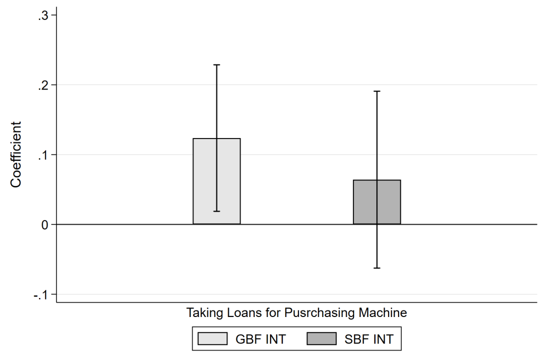
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

For policymakers, the information on the factual elements that determine lack of adoption is critical to define policy priorities; including areas that deserve further experimentation with impact evaluations that would provide more rigorous evidence of interventions. Yet, perceived obstacles do not necessarily imply that are the most relevant issues faced by the firms. Firms do not know what they don't know. Thus, we now investigate these obstacles based on factual information associated with them. We group them into three main groups: i) Financial constraints; ii) Information and knowledge; iii) Access to market and competition, which is associated with uncertainty of demand and consumer's preference.

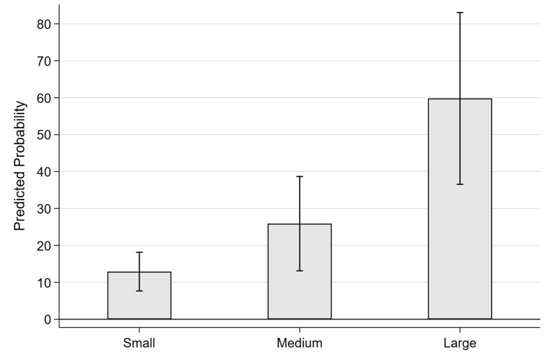
6.2 Financial Constraints

Previous studies suggest that an inefficient financial system may reduces the firm-level technology adoption within a country even if a technology is more profitable. For example, 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) provides a dynamic state model to explain that the efficiency of financial system with available technologies 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 Russia (Bircan and De Haas, 2019) or in Agriculture in Ethiopia (Abate et al., 2016).

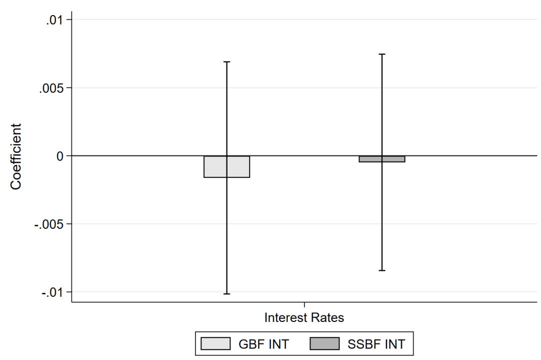
Figure 15: Loans for Purchasing Machines/Software and Interest Rates



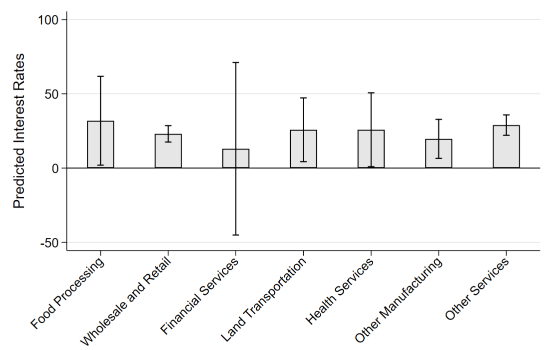
(a) Tech Adoption on Loans



(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 sector, size, and regions. Panel (b) show the predicted probability of getting loans by size groups and confidence intervals from the Probit regression 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.

Figure 15 panels (a) and (c) present the predictions of our measures of financial access - whether firms took loans and what interest rate - on the different technology indexes and on the financial access variables - panel (b) and (d) - by firm type. Taking a loan for purchasing machine is significantly associated with an 0.12 increase in the GBFs index and 0.04 for the SSBF index. In the case of the interest rates paid in existing loans, the coefficients are not statistically different from zero. Figure 15 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 15% probability of having a loan than large firms that have 60% chance. By sector and controlling for other factors, food processing and other services firms appear to face larger interest rates on their loans, but the differences are not huge across sectors.

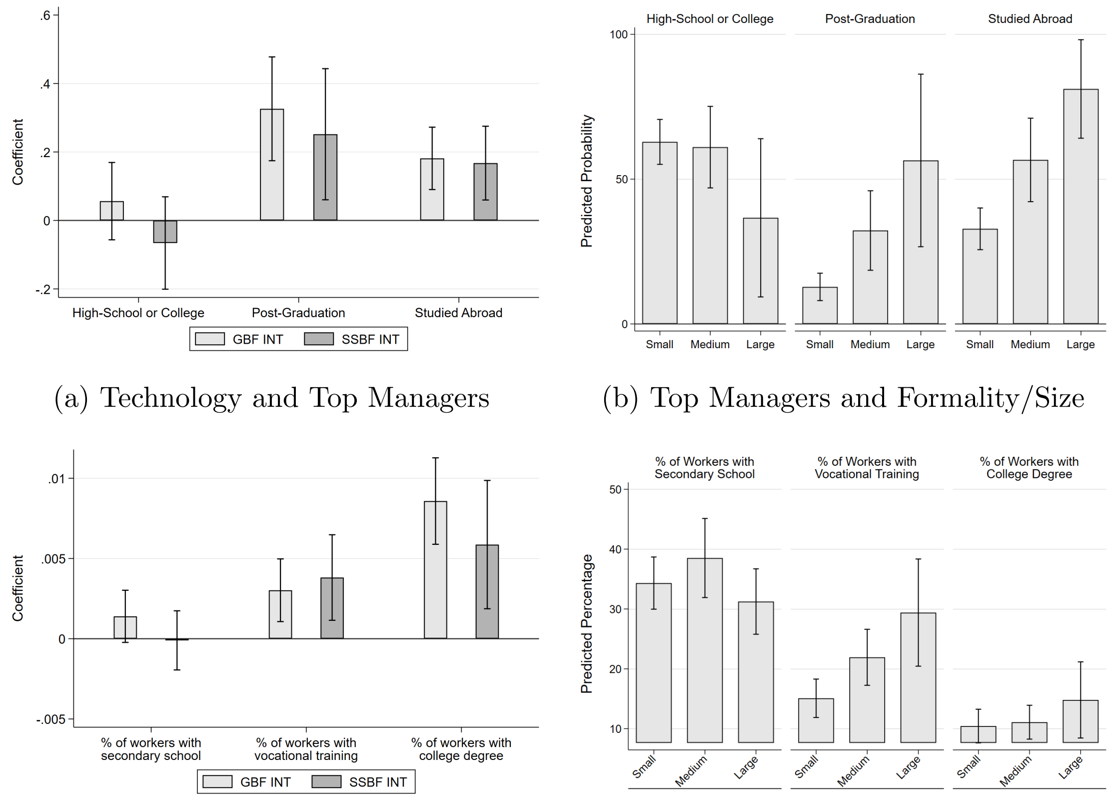
6.3 Firm capabilities

Management quality and skills

Firms' capabilities and technology adoption are also strongly associated with workers' and managers' human capital (Caselli and Coleman, 2001; Riddell and Song, 2017; Comin and Hobijn, 2004). Figure 16 shows the results of a similar exercise than before, showing human capital measures' predictions. Panels (a) and (c) focus on the correlation between managers' and workers' human capital and technology use. The coefficients of having a manager with a high school or a college degree are not statistically different from zero. In contrast, having a manager with a post-graduation is associated with an increase in the level of GBFs of 0.32 and an increase in the SBFs of 0.25. To a less extent, having a manager that studied abroad also increases the level of technology adoption for both GBFs and SBFs, with the impact varying from 0.16 (SBFs) to 0.18 (GBFs). Similarly, the effect of having a larger percentage of workers on secondary education does little to increase the sophistication of technology use; with no impact or correlation different from zero. In contrast, although minimal, a more significant percentage of workers with vocational training or college degrees is associated with increased GBFs and SBFs.

Panels (b) and (d) show that large firms are more likely to have top managers with at least a post-graduation and to have managers that studied abroad. The probability of having a manager that studied abroad is less than 40% for small firms, compared to almost 80% in large firms. Small firms are also less likely to have a larger share of workers with college degree, although the difference to large companies is small.

Figure 16: Human Capital



(a) Technology and Top Managers

(b) Top Managers and Formality/Size

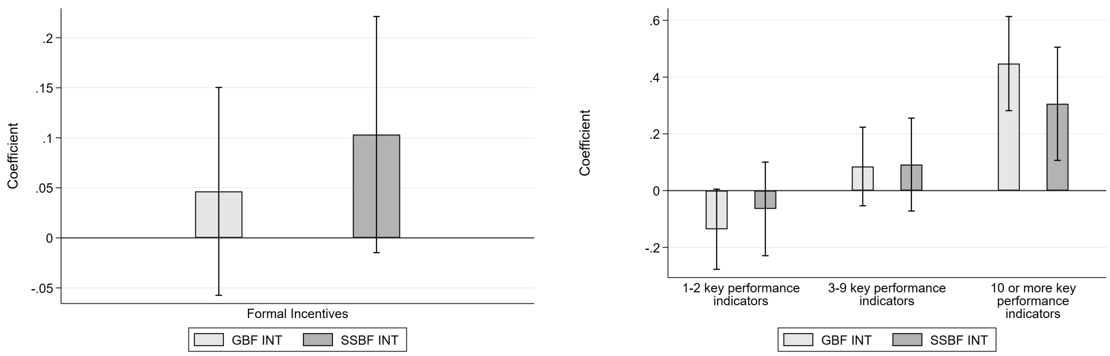
(c) Technology and Workers

(d) Workers and Formality/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 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.

The use of formal incentives and performance monitoring is positively associated with technology adoption. Innovation and the adoption of technologies are often driven by workers when they are incentivized to do so. The recent introduction of the World Management Survey (WMS), initiated by Bloom and van Reenen (2007, 2010), has permitted a quantum leap in the comparative quantitative analysis of management practices and their implications for productivity and innovation. The FAT survey allows us to compare the relationship between firms' managerial capabilities and technology adoption. The questionnaire asks if firms make use of formal incentives and the number of performance indicators they use. We use these two measures and compare them with the GBFs and SBFs indeces. Although not statistically different from zero, Figure 17 suggests that firms using formal incentives to workers have a higher index for both GBFs and SBFs at the intensive margin. Moreover, panel (b) indicates that the number of key performance indicators is positively associated with higher levels of adoption. Having 10 or more key performance indicators results in an increase of 0.44 in the GBFs and 0.30 in the SBFs.

Figure 17: Management Capabilities and Technology Adoption



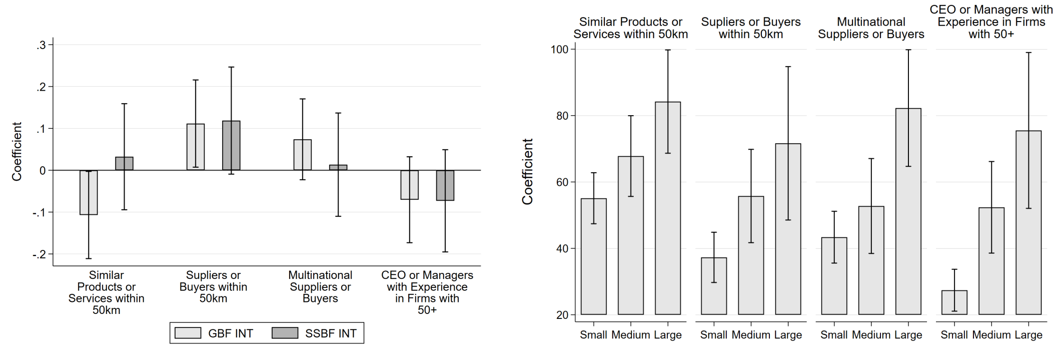
(a) Technology and Formal Incentives (b) Technology and Performance Monitoring

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.

Awareness, information and overconfidence

Figure 18 presents some potential sources of information about technology by firm size. Panel (a) shows that access to information is associated with higher technological adoption, although most of the coefficients are not statistically different from zero. Panel (b) shows the predicted probability of the various sources of information by size group. Flows of information and skills with MNEs and other firms that can facilitate adoption are larger among larger firms. 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 and other multinational firms (Alipranti et al., 2015). Larger firms are also more likely to have top managers with experience in large firms. The probability of having a manager with experience in large firms is less than 30% for small firms and up to 75% for large firms.

Figure 18: Awareness and information

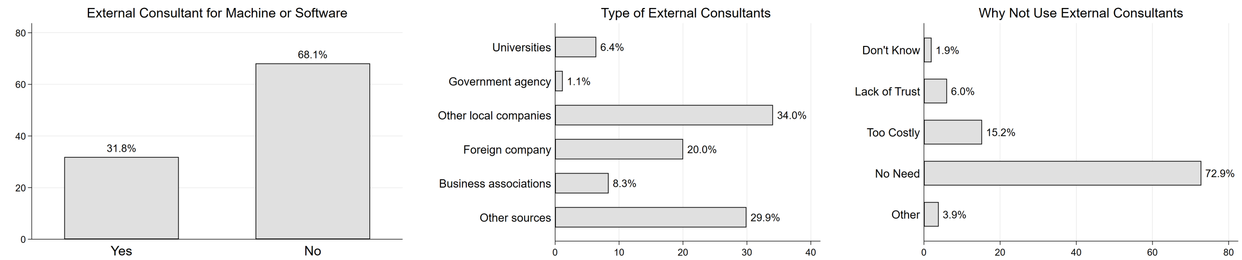


(a) Technology and information (b) Information and formality

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.

Looking at other sources of external information, the use of external consultants is very low in Malawi, but larger firms are more likely have access to external consultants on technology issues, such as the adoption of new machines or software. 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. About a third of firms in Malawi uses external consultant for purchasing machines or software (Figure 19). In addition, the type of consultants varies significantly. About 34% of firms rely on other local companies as a source of technical assistance. Meanwhile, only 6.4% of companies have worked with universities for external consultancy, suggesting the need to improve university-firms collaboration. Also, only 1.1% worked with government agencies. Among those firms that haven't used external consultants, the most common reason reported for do not access external consultants is "no need" (72.9%). However, the results also show that 15.2% find it too costly.

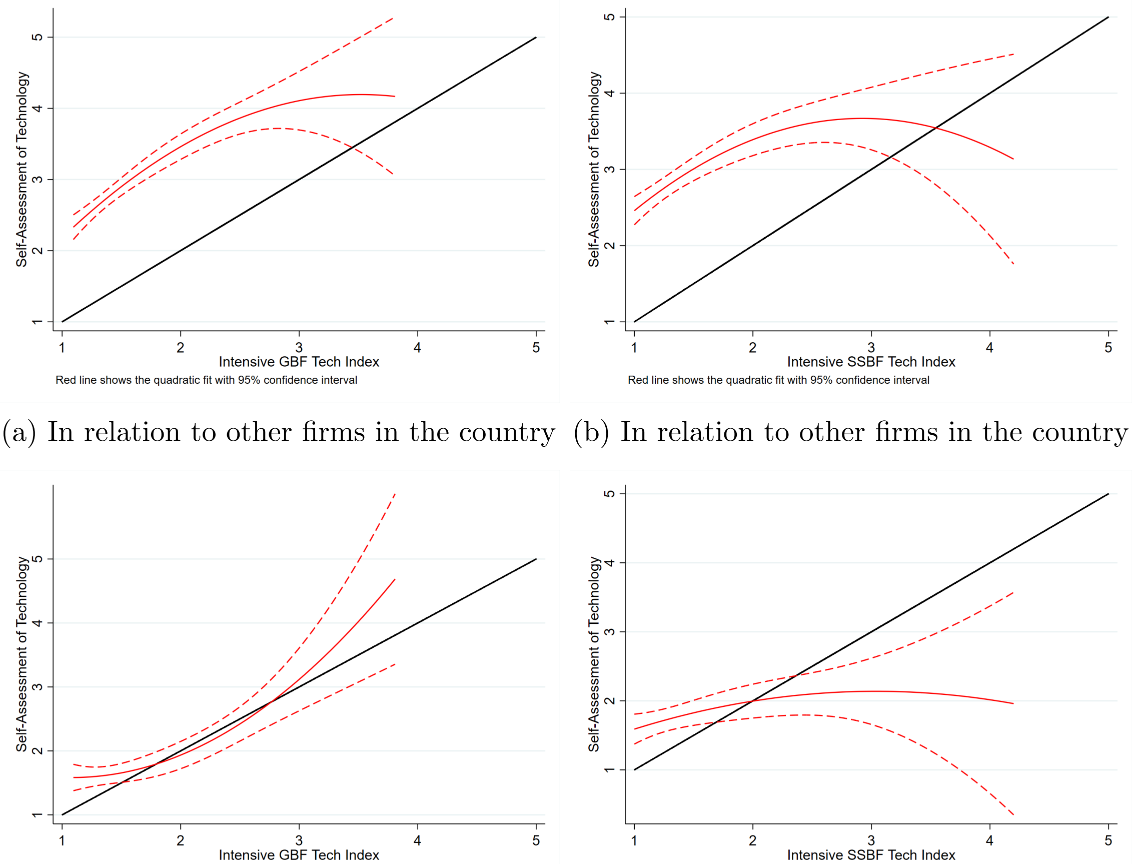
Figure 19: Access to external consultants



A final important element for non-adopting and using more sophisticated and new technologies is willingness to do so. For example, if one believes that they are already adopting more sophisticated technologies in relative terms, it is unlikely that business will adopt. Then the question is whether firms are aware of their actual technology gap. To address this question, we map their self-assessment of their technological level with the actual measurement index in the survey. The FAT survey asks for a self-assessment of technology from 1 to 10 (here re-scaled to 1 to 5) comparing the respondent's firm with firms within the country and with global technology leaders in their sector.[12] Figure 20 shows the predicted self-assessment of technology by sector specific technology adoption index with 95% of the confidence interval. The 45 degrees line shows the point where self-assessed and actual coincide. Panels (a) and (b) compare with national firms, while panels (c) and (d) to global leaders. Interestingly for most firms there is overconfidence (upper triangle) since their perception is larger than their actual level of technology. This can be a constrain to adoption and use of more sophisticated technologies. Logically this overconfidence is larger when comparing with national firms, which on average is common in firms below 3.2 index in SSBFs.

[12] We ask the self-assessment question before any of the technology adoption questions to prevent any bias in the self-assessment from potential framing.

Figure 20: 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

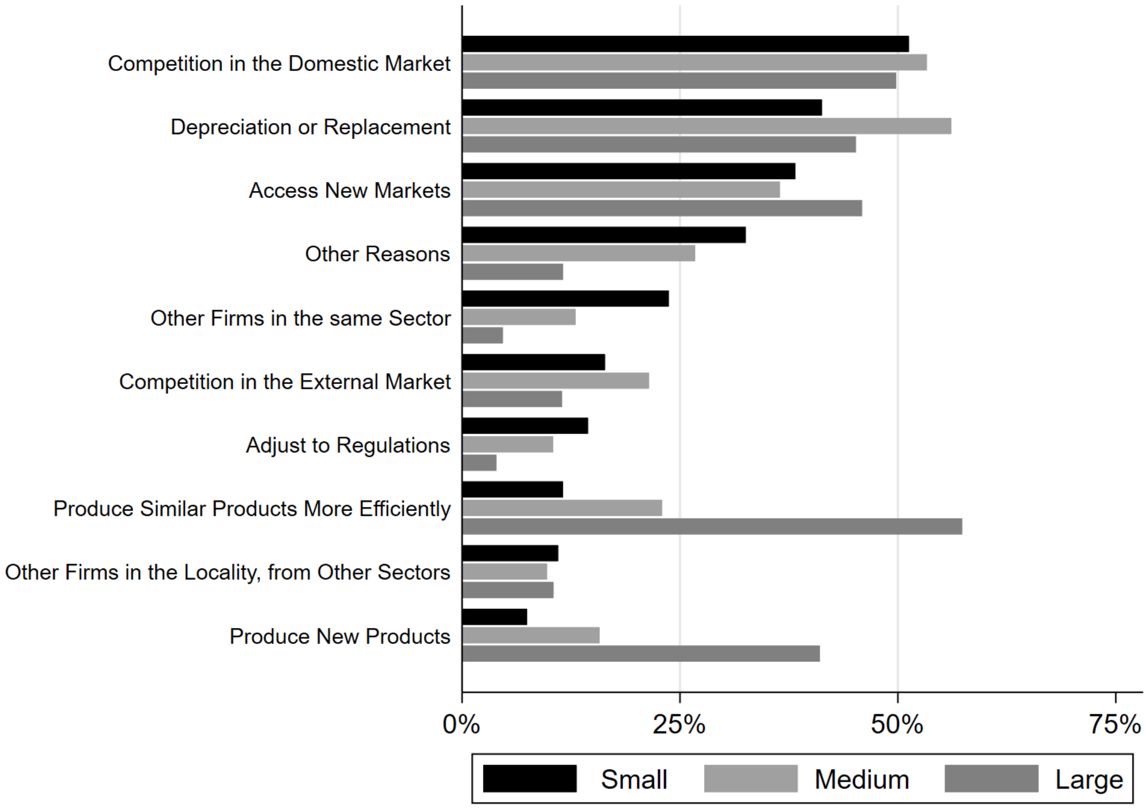
(d) In relation to the most advanced firms in the world

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 international markets and competition

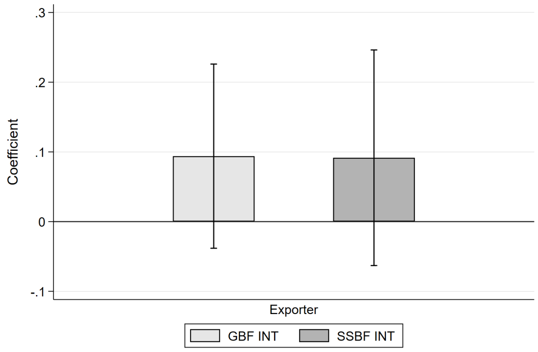
The survey also asks managers to identify the three more significant reasons to adopt new technologies. Figure 21 shows the bar charts of the main reason to adopt by firm size. About 50% of firms report "competition in the domestic market" as a key driver, followed by depreciation or replacement. This finding is consistent with the previous studies that competition may affect firm-level technologies (Milliou and Petrakis, 2011). Small firms are more likely to report "adjust to regulations" as a key driver, while more than 50% of large firms have reported that their main reason was to "produce similar products more efficiently". "Produce new products" is also more important for large firms than for small- and medium-sized companies.

Figure 21: Main reason to adopt new technologies

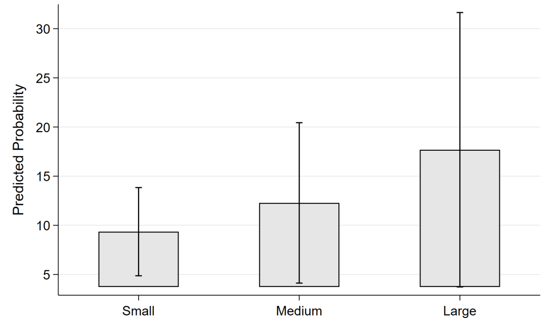


Another important driver of technology adoption is access to international markets. Increased access to international markets is likely to raise competition and provide learning opportunities, positively impacting technological adoption. Figure 22 panel (a) shows the relationship between trade status and the technology indeces. Exporting is associated with an increase in the level of GBFs and SBFs, although the coefficients are not statistically different from zero. But of course, large firms are more likely to export, which is consistent with the behavior observed across firms worldwide (Comin and Hobijn, 2004; Hobday, 1994; Rasiah and Gachino, 2005). While the predicted probability of small firms export is less than 10%, the likelihood increases up to 17% for large firms. This implies that this international trade premium is concentrated mainly in larger firms. Figure 23 shows the index for the different GBFs differential between exporters and non-trading companies. Exporting companies use more advanced technologies for general business functions, although the difference is relatively small.

Figure 22: Association between exporters and technology adoption



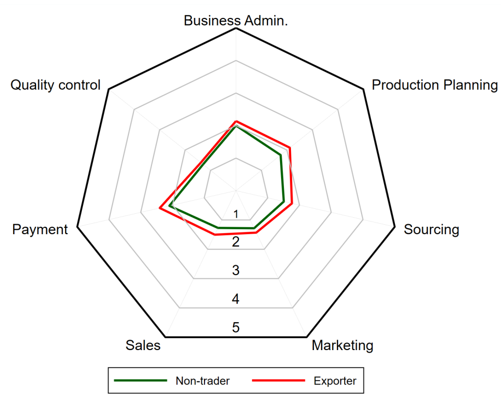
(a) Technology and export



(b) Export 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.

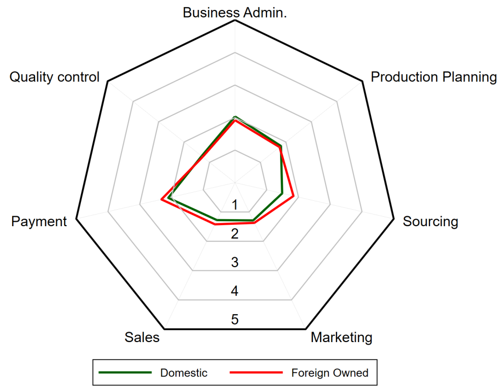
Figure 23: Exporters



(a) Intensive Margin

We also repeat the exercise of decomposing the technology index between domestic and foreign owned companies, those with more than 50% foreign ownership. Interestingly and despite the previous results of the larger technology indices of firms with managers that have worked in MNEs, the differences between domestic and foreign owned companies are small.

Figure 24: Domestic and foreign owned companies

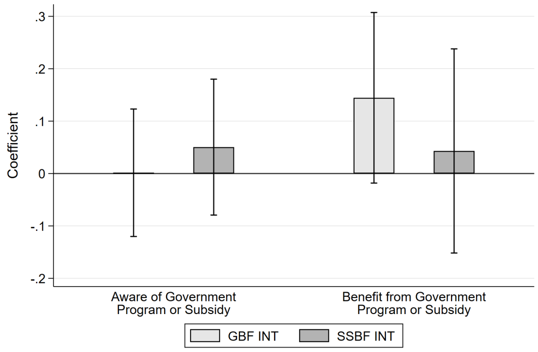


(a) Intensive Margin

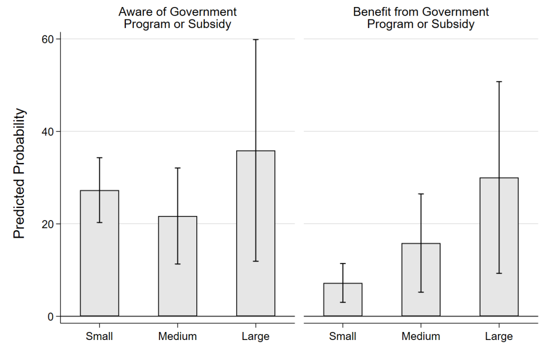
6.5 Access to government support

Large firms benefit more from government programs or subsidies in Malawi. Panel (a) in Figure 25 shows the predicted probability of being aware or benefiting from government programs, while panel (b) describes the predicted probability by size group. Panel (a) suggests that the coefficients of the association between awareness or benefit of program subsidies and technology adoption are not statistically different from zero. In contrast, the probabilities are much larger for large firms, both in terms of awareness and benefiting from those programs. Larger firms are about 35% likely to be aware of government support and 30% to benefit, while less than 10% of small firms benefit from government programs. These results suggest that it is important to disseminate government support programs to facilitate adoption, especially among medium and small-size firms.

Figure 25: Awareness of government program and subsidy



(a) Predicted probability



(b) Size

Note: Panel (a) shows the predicted probability of the awareness of government program or subsidy 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 size 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 add the elements discussed so far in a regression framework to analyze which variables are more correlated with technology use. Table 5 shows the results for two technology indices, controlling for size, sector, and regions. We use only factual variables. Technology adoption is significantly and positively associated with managers with a college degree or more. However, although both coefficients are positive, managers' education is only statistically significant for the GBFs index. Overall, however, it is hard to explain technology use, and these variables explain only one-third of the total variance in technology.

Table 5: Technology adoption is associated with access to knowledge and information

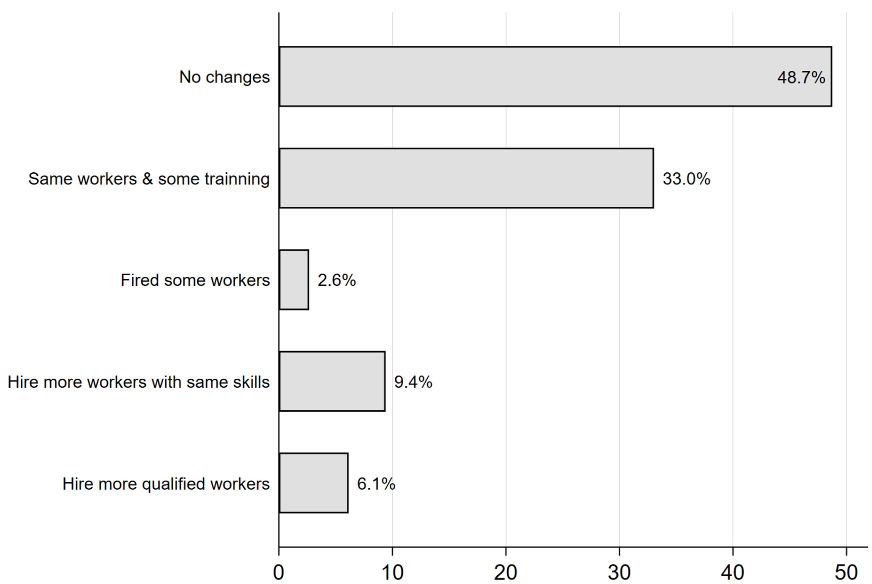
VARIABLES	**GBF Int**	**SBF Int**
Loan for Machine	0.091	0.069
	(0.061)	(0.053)
Similar Products in 50km	-0.050	-0.004
	(0.041)	(0.052)
Supplier and Buyers in 50km	0.046	0.060
	(0.043)	(0.053)
Supplier or Buyer MNCs	0.050	-0.030
	(0.041)	(0.050)
Manager Experience in Large Firms	-0.066	-0.048
	(0.045)	(0.054)
Use of External Consultant	0.046	0.078
	(0.047)	(0.059)
Benefit from Government Support	0.048	0.010
	(0.079)	(0.091)
Manager with College or More	0.101***	0.074
	(0.035)	(0.056)
% of Workers with College	0.004***	0.002
	(0.001)	(0.002)
Ln (Employment 2018)	0.075***	0.097***
	(0.017)	(0.018)
Constant	0.008	0.047
	(0.061)	(0.082)
Observations	392	292
R-squared	0.519	0.446
Sector FE	YES	YES
Region FE	YES	YES

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

7 Technology and employment

In a final exercise, we investigate the relationship between technology adoption and employment. When asked about how firms adjust their labor to the adoption of new technologies through the acquisition of a new machine, equipment, or software, about 48.7% of firms suggest that they do not change the number of workers, and roughly 33% indicate that they offer some training to current workers (Figure 26). Only a small number of firms, 2.6%, 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 (9.4%) or hire more workers with more qualified (6.1%).

Figure 26: How firms self-report their adjustments to new technologies?



We also investigate if there is an association between employment growth and the use of more advanced technologies. Table 6 shows a positive and statistically significant association between growth (between 2016 and 2018) and technology adoption across different measures of technology and controlling for the firm's initial size, age, sector, region, foreign ownership, and exporting status. The association is weaker in GBFs and more significant for SBFs, suggesting that the impact on growth is more related to the intensive use rather than simply adopting more sophisticated technologies.

When analyzing the association between technology adoption and growth for specific general business functions, we observe a positive association with most business functions. However, most coefficients are not statistically different from zero. Figure 27 shows that this

Table 6: Employment growth and tech adoption (Intensive Margins)

	(1)	(2)	(3)	(4)	(5)	(6)
ABF Int	0.109*	0.121*				
	(0.059)	(0.065)				
GBF Int			0.098*	0.105*		
			(0.056)	(0.062)		
SBF Int					0.119**	0.150**
					(0.049)	(0.060)
Ln (Employment 2016)	-0.072***	-0.080***	-0.070***	-0.076***	-0.060***	-0.082**
	(0.023)	(0.027)	(0.023)	(0.027)	(0.023)	(0.032)
Constant	0.107	0.119	0.117*	0.139	0.068	0.115
	(0.067)	(0.092)	(0.064)	(0.091)	(0.064)	(0.103)
Observations	440	433	440	433	331	328
R-squared	0.058	0.101	0.056	0.098	0.047	0.115
Firm characteristic	NO	YES	NO	YES	NO	YES
Sector FE	NO	YES	NO	YES	NO	YES
Region FE	NO	YES	NO	YES	NO	YES

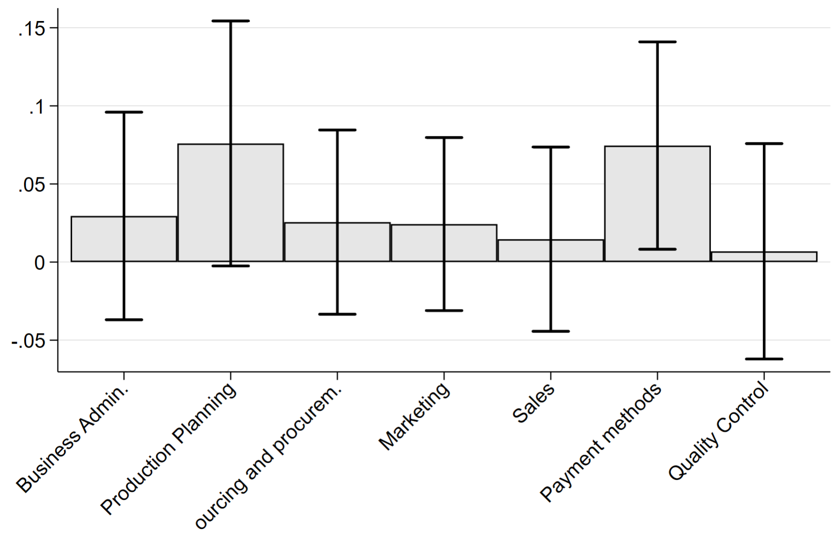
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

association is more significant and more precisely estimated for the intensive use of more advanced digital technologies applied to payment methods and production planning (e.g., Specialized Software and ERP systems).

One crucial question for the impact of technology on employment is how the adoption of more sophisticated technologies affects the workers' composition towards more skilled workers; the skill bias technological change hypothesis. To investigate this relationship, we analyze the correlation between the technology index and changes in the firm's skill composition 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 includes workers in low-skilled occupations (clerks, production, and service workers). We then compare this share between 2016 and 2018 and use it as a dependent variable. Table 7 shows a positive association between changes in the skill intensity and the level of ABFs and GBFs technology, controlling for the firm's initial size; although positive, the correlation is not significant. In contrast, the association between skill intensity and SBFs is negative. This association does not infer a causal relationship between technology and skill intensity. Still, it has an important implication suggesting that firms with higher levels of SSBFs technologies generated more jobs on average and increased workers' share of unskilled workers in their payroll.[13]

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

Figure 27: 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.

Table 7: Change in the share of high-skill occupations and tech adoption

	(1)	(2)	(3)	(4)	(5)	(6)
ABF Int	0.014	0.024				
	(0.029)	(0.041)				
GBF Int			0.013	0.023		
			(0.028)	(0.037)		
SBF Int					-0.029*	-0.039*
					(0.017)	(0.020)
Ln (Employment 2016)	0.007	0.010	0.007	0.010	0.021***	0.027***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.008)	(0.010)
Constant	-0.066**	-0.057	-0.065**	-0.055	-0.037	-0.047
	(0.028)	(0.051)	(0.026)	(0.048)	(0.023)	(0.056)
Observations	440	433	440	433	331	328
R-squared	0.008	0.053	0.008	0.053	0.033	0.097
Firm characteristic	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

8 Concluding Remarks

Adopting more sophisticated technologies is of utmost importance for Malawi to reduce its productivity gap and reduce poverty. This paper has used a novel approach to measure technology adoption and has provided a very granular view of technology adoption. The results suggest a large gap between Malawian formal firms and the technological frontier, both in general business functions and sector-specific business functions. Overall, irrespective of size, sector, or region, most enterprises rely on basic technologies, perform most of the operations manually, or have extensive face-to-face interactions.

The paper also discusses the main obstacles to technology adoption in the country, finding that uncertainty and lack of demand, lack of capabilities, and access to finance are the three more significant barriers to adoption and diffusion. The findings also suggest that small- or medium-sized companies are less benefited or aware of government programs or subsidies. Therefore, the government has a critical role in supporting financial access and information access to its programs. Simultaneously, it needs to provide information to firms on what technologies are available, support training on workers and management skills, and support technology upgrading. The COVID-19 pandemic has stressed the need to accelerate technology adoption to cope with some of the lockdown restrictions and avoid potential longer demand effects. Clearly, Malawian firms were not ready.

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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:

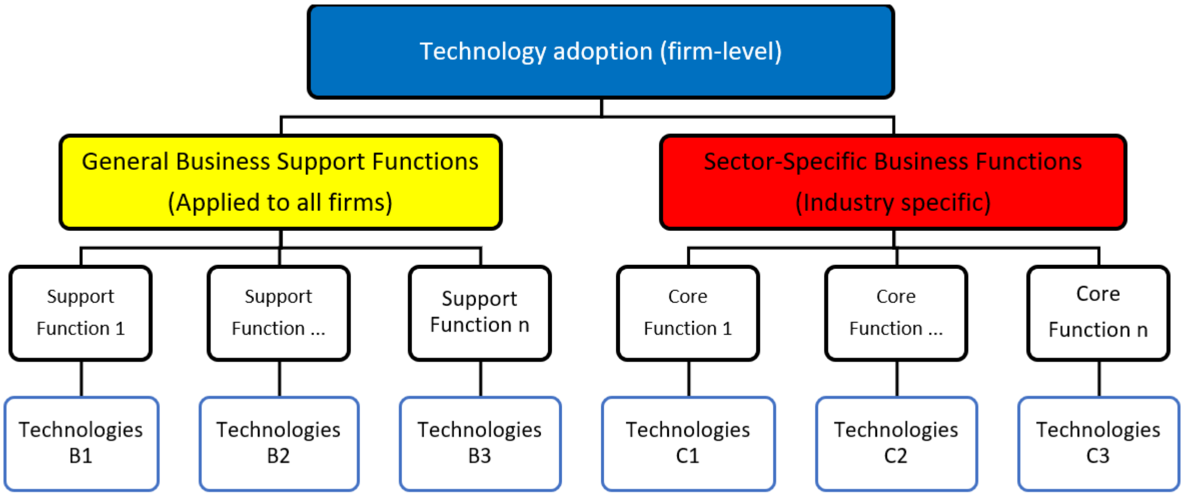
- Module A– Collects general information about the characteristics of the establishment.
- Module B – Covers the technologies used in eight generic business functions.
- Module C – Covers the use of technologies for functions that are specific to each of ten industry and services sectors
- Module D – 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 $R_f \leq N_f$.[14] 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 technology index used in this paper 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

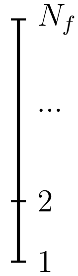
$$T_{f,j}^{INT} = 1 + 4 * \frac{r_{f,j}^{INT}}{R_f} \tag{1}$$

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.

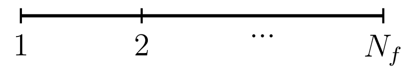
The technologies in other business functions may have a horizontal relationship (Romer, 1990), depicted in panel B. In horizontal structures, the use of less sophisticated technologies

[14]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 tasks groups.

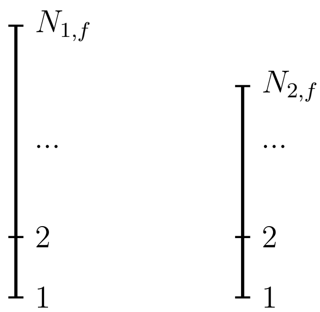
Figure B1: Different technology sophistication structures



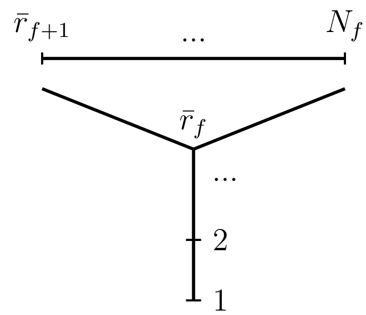
(a) Quality Ladder



(b) Horizontal Relationship



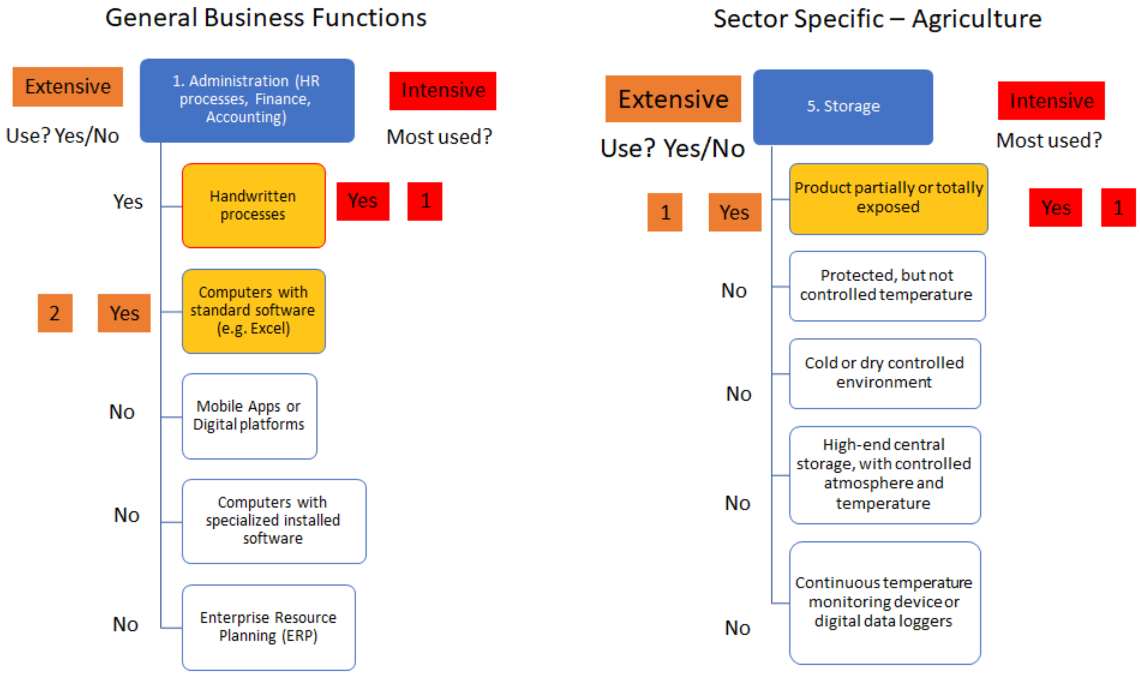
(c) Hybrid I



(d) Hybrid II (Tree)

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: Tech adoption and firm's characteristics

VARIABLES	**GBF Int**	**SBF Int**
Services	0.128***	0.155***
	(0.034)	(0.044)
Firm age (6-10)	0.045	0.076
	(0.047)	(0.054)
Firm age (11-15)	-0.033	-0.024
	(0.053)	(0.052)
Firm age (15+)	0.023	-0.014
	(0.044)	(0.055)
Multinationals	0.081*	0.072
	(0.044)	(0.062)
Exporter	0.018	-0.041
	(0.053)	(0.068)
Ln (Employment 2018)	0.129***	0.154***
	(0.013)	(0.013)
Constant	-0.061	-0.244***
	(0.050)	(0.057)
Observations	441	333
R-squared	0.370	0.409
Region FE	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)**
GBF Int	1.098**	
	(0.459)	
SBF Int		1.008**
		(0.469)
Ln (Employment 2018)	-0.028	0.033
	(0.082)	(0.105)
Constant	14.784***	14.396***
	(0.487)	(0.544)
Observations	325	251
R-squared	0.157	0.223
Sector FE	YES	YES
Region FE	YES	YES

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

Table C3: Sector Specific Functions heterogeneity

VARIABLES	**GBF Ext**	**GBF Int**
Medium	0.281**	0.326***
	(0.111)	(0.084)
Large	0.568***	0.706***
	(0.183)	(0.117)
Services	0.199*	0.191***
	(0.110)	(0.066)
Lilongwe	-0.185*	-0.009
	(0.105)	(0.076)
Mzimba	-1.059***	-0.359***
	(0.101)	(0.125)
Mzuzu	-0.877***	-0.281***
	(0.180)	(0.071)
Constant	2.573***	1.273***
	(0.122)	(0.061)
Observations	450	450
R-squared	0.166	0.281

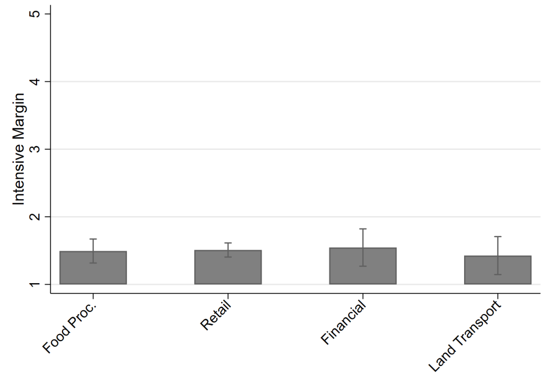
Note: Robust standard errors in parentheses. *** p < 0.01, ** p< 0.05, * p <0.1

Table C4: Sector Specific Functions heterogeneity

VARIABLES	**SSBF Ext**	**SSBF Int**
Medium	0.504***	0.260**
	(0.121)	(0.108)
Large	0.550**	0.823***
	(0.279)	(0.108)
Apparel	1.060**	0.047
	(0.502)	(0.371)
Motor vehicles	-0.774***	-0.432***
	(0.195)	(0.120)
Pharmaceuticals	-0.395	-0.075
	(0.449)	(0.236)
Wholesale or retail	-0.210	-0.014
	(0.212)	(0.103)
Financial services	0.519**	0.036
	(0.252)	(0.155)
Land transport	-0.404	-0.104
	(0.321)	(0.162)
Health services	-0.267	0.346**
	(0.207)	(0.142)
Other manufacturing	0.083	-0.238**
	(0.231)	(0.105)
Constant	2.347***	1.345***
	(0.193)	(0.088)
Observations	340	337
R-squared	0.207	0.351
Region	YES	YES

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

Figure C1: SSBF - Predicted Values



(a) 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.