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ABSTRACT

We collect detailed data on the technologies used in a comprehensive set of business functions in a representative sample of firms in Vietnam, Senegal, and the Brazilian state of Ceará, and construct measures of technology sophistication at the business function and firm levels. There is a large variance of sophistication across firms, but we find that the variance of technology sophistication across the business functions of a firm (within-firm variance) is 2.8 times larger. We develop a model of technology adoption with heterogeneity in adoption costs across business functions and with non-homothetic production that induces heterogeneity in the marginal value of technology sophistication across functions. The model predicts a stable cross-firm relationship between sophistication in the business function and firm-level technology that we call the technology curve. We find that the slopes of technology curves differ greatly across business functions and that curves account for one third of within-firm variance in sophistication. A development accounting exercise shows that cross-firm variation in sophistication measures accounts for thirty percent of cross-firm differences in productivity.

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1 Introduction

Economists and sociologists have long been interested in the measurement of technology, among other reasons, to characterize the technological sophistication of firms. The seminal studies by Ryan and Gross (1943) and Griliches (1957) on the diffusion of hybrid varieties of corn introduced what became the dominant approach to measuring technology through a binary variable that reflects whether a potential adopter uses an advanced technology.[1] Since then, it has become a common practice to characterize the technological sophistication of a firm by the presence of a few (often just one) advanced technologies.[2] Recent efforts such as the Canadian SAT have added detail to the characterization of technology within firms by increasing the number (between 41 and 50, depending on the round) of advanced technologies that firms are asked about.

Yet despite all these efforts, existing measures of technology still do not provide a comprehensive characterization of technology within firms. They fall short in several ways. First, the number of technologies covered in the surveys is rather limited when compared to the number of technologies actually involved in production. Second, the focus on the presence of advanced technologies makes it impossible to understand how production takes place in companies that do not utilize state-of-the-art technologies. This concern is particularly relevant in developing countries where advanced technologies are less widely diffused. Third, since the unit of analysis is the firm, existing measures are not well suited to study which business functions benefit from each technology. This drawback is particularly problematic for general purpose technologies that can be used across a range of business functions. Finally, most existing surveys fail to enquire how intensively a technology is used in the firm, and therefore cannot shed any light on whether a technology that is measured as present is used widely in the firm.[3]

The first goal of this paper is therefore to construct a new, comprehensive set of technol-

[1] Measures of technology based on this approach have been used to study, among other topics, the patterns of technology diffusion (e.g., Mansfield, 1961), the drivers of adoption (e.g., Foster and Rosenzweig, 1995; Duflo, Kremer and Robinson, 2011; Suri, 2011; Atkin, Khandelwal and Osman, 2017), the effect of technology on productivity (e.g., Bartel, Ichniowski and Shaw, 2007; Juhász, Squicciarini and Voigtländer, 2020) and on wages (e.g., Krueger, 1993; DiNardo and Pischke, 1997).

[2] For example, Davies (1979) studies the diffusion of 26 manufacturing technologies but, typically, each technology is relevant only in one narrow sector, Trajtenberg (1990) measures the presence of CAT-scanners in hospitals, Brynjolfsson and Hitt (2000); Stiroh (2002); Bresnahan, Brynjolfsson and Hitt (2002); Akerman, Gaarder and Mogstad (2015) measure the presence of some ICTs such as computers or access to internet. This practice has been adopted in surveys of ICT conducted by the statistical offices in a number of advanced economies, including the US Census Bureau (ICTS and ABS), the Eurostat (Community Survey of ICT Usage), and Statistics Canada (Survey of Advanced Technology (SAT).

[3] One exception is Mansfield (1963) and subsequent papers, which have studied the diffusion of a specific technology within a firm, and so provide a proxy for the intensity with which the technology is used at the firm level.

ogy measures that overcome these limitations. Our technology measures are based on the Firm-level Adoption of Technology (FAT) survey that we have designed and administered to a representative sample of establishments in Senegal, Vietnam, and the Brazilian state of Ceará.[4] With the help of over 50 sector and technology experts, we have created a list of the key business functions carried out by firms and, for each of them, we have listed the technologies that companies can use to carry out the main tasks in each business function, from the most basic to the most sophisticated. The FAT survey covers seven general business functions (GBF) that are common to all companies and, for twelve large sectors, FAT also covers sector-specific business functions (SSBF). In total, FAT covers 63 business functions and 305 technologies associated with them.[5]

FAT asks firms to list the technologies that are used in each business function and, among these, which one is the most widely used. With this information, we construct business function-level measures of the sophistication of the most widely used technology. The scope and structure of FAT ensure that our technology sophistication measures have three key features. First, they are informative about the sophistication of the technologies used in all firms, even those that do not use advanced technologies. Second, they reflect how intensively a technology is used, not just its presence. Third, they provide a very granular characterization of the technological landscape across the different business functions of a firm.

We use the FAT dataset to explore technology sophistication across firms, across the business functions of the firm, *within-firm*, and the relationship between firm-level productivity and measures of technology sophistication. We document cross-firm differences in sophistication that are at least as large as cross-country differences. Observable firm characteristics such as size, exporting and multinational status are positively associated with the average technology sophistication of a firm. Both at the national and regional levels, there is a positive association between technology sophistication and economic development.

The most original insights from FAT, however, concern the use of technology within firms. Since the unit of observation in FAT is the business function, our data provides a granular characterization of the sophistication of technologies used in a establishment. This wealth of information allows us to pose new questions. We first explore whether technology sophistication is relatively uniform across the business functions of a firm. We document that the within-firm variance in technological sophistication is 2.8 times larger than the cross-

[4] Our unit of analysis is the establishment. Throughout the paper we use the terms firm and establishment interchangeably.

[5] See Table A.1 for a comparison with other firm-level surveys. For Senegal and Brazil we consider only 59 BFs because the sector-specific questionnaire for leather and footwear was prepared after the beginning of the data collection in those two countries.

firm variance in sophistication. This finding debunks the notion that technology is relatively uniform inside firms. Within-firm variance in sophistication covaries positively with average firm sophistication and it is uncorrelated with firm size or age, once we control for average sophistication.

To understand the sources of variation in technology sophistication within firms, we develop a model of optimal technology adoption with heterogeneity in the marginal cost of technology sophistication across functions, and with a non-homothetic aggregation of the vector of business-function technology sophistication levels into the firm-level technology index. In our setting, firms achieve higher levels of the technology index, by raising the technological sophistication at different rates across business functions. As a result, more sophisticated firms have greater variance in sophistication across business functions, as observed in the data. Additionally, the model predicts the existence of a stable *cross-firm* relationship between the sophistication in a business function and the firm-level technology index. We name this relationship the *technology curve*.

Using the FAT data, we estimate the technology curves. Our key finding is that there is large variation in the slopes of technology curves across business functions. This finding confirms that firms choose to upgrade the technology at different rates across business functions, as they become more sophisticated. Furthermore, despite their simplicity, technology curves explain 32 percent of the within-firm variance in technology sophistication.

We conclude our analysis by connecting firm-level labor productivity and sophistication measures. Our estimates show that both average firm sophistication and within-firm variance in technology sophistication are positively associated with firm-level productivity. To quantify this association, we conduct a development accounting exercise that reveals that cross-firm differences in technology sophistication measures account for between 24% and 30% of the gap between firms at the top and bottom deciles of the productivity distribution.

In addition to the studies on technology measurement cited above, our analysis is related to several strands of the literature. A number of studies have investigated the relationship between technology and productivity at different levels of aggregation and with varying degree of comprehensiveness in the technologies covered. Comin and Hobijn (2010) and Comin and Mestieri (2018) explore the effect of the adoption of a wide range of technologies on the evolution of the distribution of productivity growth across countries over the last 200 years. Various articles have linked the adoption of technologies (most prominently information technologies) to the variation in productivity growth across sectors and over time.[6] A third strand of research, closer to ours, has focused on understanding productivity at the

[6] See e.g., Comin (2000), Jorgenson et al. (2005), Jorgenson, Ho and Stiroh (2008), Oliner, Sichel and Stiroh (2007), Van Ark, O'Mahoney and Timmer (2008).

firm level, but, unlike us, it considers a limited number of technologies.[7] Their focus on a limited number of technologies often prevents these studies from capturing how, due to complementarities between technologies, a shock that induces firms to adopt one technology may have broader effects on the firm's technological landscape and on its productivity. Comprehensive datasets such as FAT, combined with models such as the one we develop, enable us to disentangle the direct and indirect effects of technology adoption on productivity.

There are interesting parallels between our contribution to measurement of technology and recent efforts to measure management practices. A long tradition in management and economics has documented the use of specific management practices in (typically) a small number of companies (often just one!). Pathbreaking studies by Bloom and Van Reenen (2007) and Bloom et al. (2019) have extended the scope of this literature by conducting firm-level surveys in a large number of firms across many countries to measure the quality of management practices along several dimensions connected to operations, planning, monitoring and human resources.[8] Bloom and Van Reenen (2007) compute a firm-level index of management quality as the average score across 18 dimensions and study how the index is related to firm productivity.

FAT shares with the WMS and MOPS the goals of obtaining rich, detailed information about firms using survey methods, and connecting measures of the sophistication of managerial practices or technology with firm-level productivity. There are, however, important differences between our paper and this literature on management practices. Beyond the obvious conceptual differences between technologies and managerial practices, and the differences in survey coverage,[9] the main difference is that we have a genuine interest in studying differences in the sophistication of technology across the business functions of a given firm. This interest is reflected in the design and implementation of the survey, in the measurement of technology sophistication at the business function level, and in our study on how the vector of business functions technology sophistication aggregates into a firm-level technology index.

[7]For example, Hubbard (2003) studies the effects of adopting on-board computers in trucks, Bartel, Ichniowski and Shaw (2007) study the effects of the adoption of computer numerically controlled (CNC) machines and computer-aided design (CAD) software in the productivity of valve manufacturing. Hjort and Poulsen (2019) analyzes how the access to fast Internet connection increases firm entry, productivity, and exports in African countries. Gupta, Ponticelli and Tesei (2020) study how the adoption of cellphones by Indian farmers increased their productivity by reducing their informational barriers.

[8]These surveys include the World Management Survey (WMS) and the Management and Organizational Practices Survey (MOPS). The WMS is a telephone based survey that uses double blinded methodologies. MOPS is an online and paper based survey.

[9]While management practices refer to establishing routines to deal with decision processes, technologies are often embodied in machines and software or represent processes that typically require certain equipment and technological knowledge. FAT covers a wider range of business functions (i.e. both general and sector-specific) and technologies as it intends to be comprehensive in both of these dimensions. WMS and MOPS cover many more firms and countries than FAT has covered so far.

Our findings with regards to within-firm technology, including the magnitude of within-firm variance, the existence of technology curves, and their importance for within-firm variance in sophistication, are all novel.

The rest of the paper is structured as follows. Section 2 presents the FAT survey. Section 3 explains how we use the information collected with the FAT survey to construct technology sophistication measures. Section 4 analyzes technology sophistication across firms. Section 5 analyzes technology sophistication within firms. Section 6 studies the relationship between technology sophistication measures and firm productivity. Section 7 concludes.

2 The Survey

The FAT survey ("the survey" henceforth) collects detailed information for a representative sample of firms about the technologies that each firm uses to perform key business functions necessary to operate in its respective sector. In what follows we describe in detail the survey design and implementation.[10]

2.1 Structure

The survey is composed of five modules. Module A collects information on general characteristics about the firm.[11] Modules B and C cover the technologies used by the firm. Module D focuses on barriers and drivers of technology adoption, while module E gathers information about the firm's balance sheet and employment.

The survey differentiates between general business functions (module B) which comprise tasks that all firms conduct regardless of the sector where they operate; and sector-specific business functions (module C) which are relevant only for firms in a given sector. All firms in our sample respond to module B, but only those firms belonging to the sectors for which we have developed a sector-specific module respond to C. To attain a wide coverage that allows a meaningful study of sector-specific technologies, we develop sector-specific modules for ten significant sectors in the economy.[12] These sectors have been selected to cover all three industries (agriculture, manufacturing, and services) and based on their share in aggregate value-added, employment and number of establishments.

[10]See Appendix A for more details.

[11]The survey is designed, implemented, and weighted at the establishment level. For multi-establishment firms, the survey targets the establishment randomly selected in the sample.

[12]The ten sectors for which we have developed sector-specific modules are: agriculture (crops and fruits), livestock, food processing, wearing apparel, automotive, pharmaceutical, retail and wholesale, banking services, land transport services, and health services.

2.2 Technology grid

To design modules B and C, we determine the business functions covered and the list of technologies that can be used to implement the key tasks in each function. We call the resulting structure the grid. The grid in FAT has three characteristics. First, it is comprehensive. It includes the main business functions and the full array of technologies in each function, from the most basic to the most advanced technologies available. Second, the business functions and technologies in the grid are relevant to all firms within any given sector. For example, the business functions and technologies in the grid for crop agriculture should allow us to characterize the technologies used both by large producers of soybeans in Brazil, and small producers of rice in Vietnam. Third, the technologies are precisely defined so that their use in a firm can be objectively established by respondents and enumerators.

To construct the grid, we followed three steps. First, we conducted desk research reviewing the specialized literature. Second, we held meetings with World Bank experts in each of the sectors covered. Third, we reached out to external consultants with significant experience in the field (at least 15 years).[13] Over 50 experts participated in the construction of the technology grid. The resulting grid is composed of 7 general and 56 sector-specific business functions and a total of 305 technology/business functions pairs. Figure 1 presents the general business functions considered in the survey and the possible technologies that can be used to conduct each of them. Figure 2 presents the grid for food-processing, one of our SSBFs.[14]

In addition to identifying the key business functions and relevant technologies, experts also provided us with a ranking of the technologies in each business functions based on their sophistication. The sophistication of a technology can be manifested in (i) the capacity to conduct more tasks, (ii) tasks of greater difficulty, or (iii) to carry tasks with greater accuracy, precision or speed. Naturally, technological sophistication is correlated with the novelty of the technology.

2.3 Technology questions

The survey contains two types of questions about the technologies used by the firm. First, FAT asks whether the firm uses each of the technologies in the grid to conduct the tasks of

[13]The external experts in agriculture and livestock were agricultural engineers and researchers from Embrapa-Brazil. For food processing, wearing apparel, automotive, pharmaceutical, transport, finance, and retail, as well as for the GBFs, we relied on senior external consultants selected by a large management consulting organization. For health, the team relied on consultants and physicians with practical experience in both developing countries and advanced economies.

[14]The grids for the GBFs and the eleven SSBFs are available in section A.1 of the Appendix A .

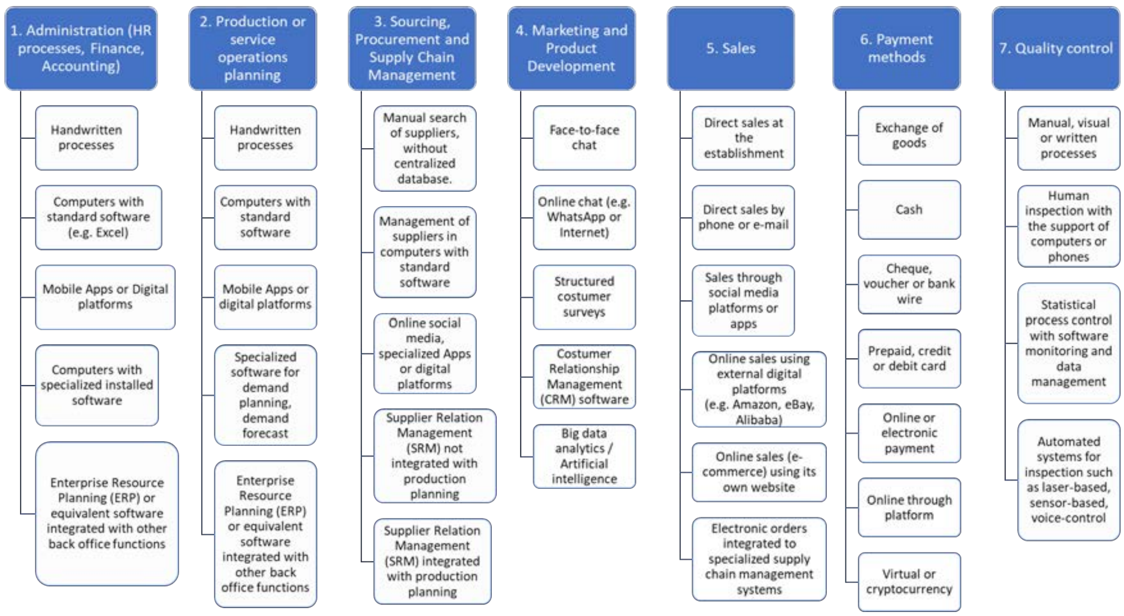


Figure 1: General Business Functions and Their Technologies

the particular business function. One of the options offered in all the business functions is "other technologies." The frequency that respondents declare that "other" technologies are used in the business function allows us to assess the comprehensiveness of the technologies in the grid. Firms use "other" technologies in 3.65% of the business functions which confirms that the technologies in the grid are comprehensive.[15]

After determining the technologies that are used by the firm in a business function, the survey asks which of these technologies is the most widely used in the business function.[16] In this way, the first set of questions works as a filter that defines the options available to the respondent when answering about the most used technology.

2.4 Sampling and survey implementation

Several factors were taken into consideration to decide where to implement the FAT survey in the first round. We targeted countries in different continents (Asia, Africa, and Latin America) with different levels of income. We required the existence of a good quality sampling frame and funding available to cover the data collection. Brazil, Senegal, and Vietnam

[15]"other" is the most widely used technology in 0.8% of the business functions.

[16]In the pre-pilot stage, we experimented with survey designs that asked about the fraction of time/output/processes that were conducted with each of the technologies in the business function. We decided against using this approach to reflect the intensity of use of technologies because it was harder to answer precisely by respondents and as a result led to a more subjective interpretation that made harder the comparability of answers across business functions and companies.

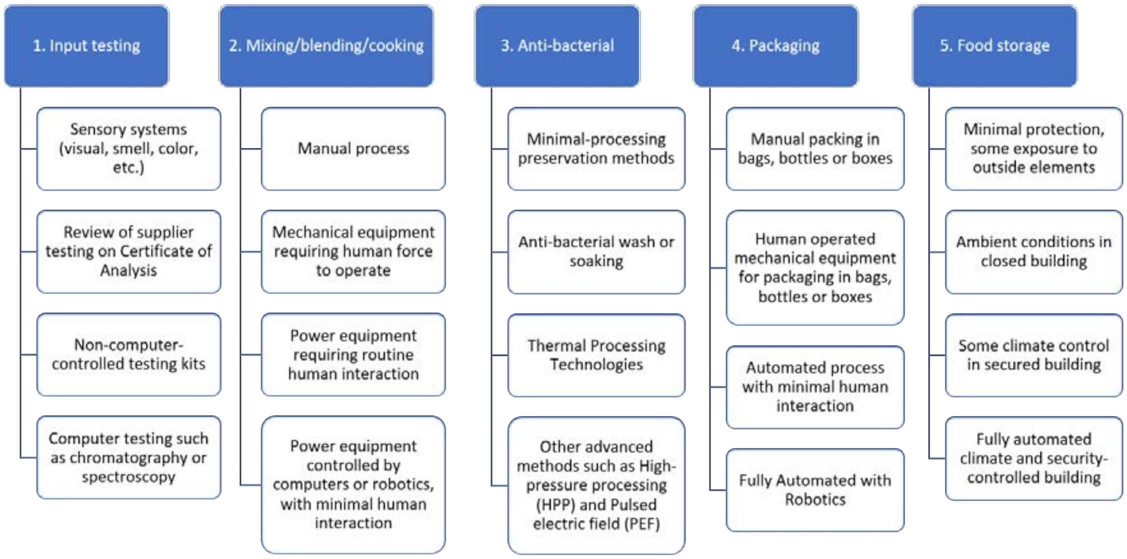


Figure 2: Sector Specific Business Functions and Technologies in Food Processing

satisfied all these requirements. Our sample is nationally representative for establishments with 5 or more employees.[17] For each country, the sampling frame is based on the most comprehensive and updated establishment-level census data available from the respective National Statistical Office (NSOs) or similar administrative information.[18] The survey is stratified along three dimensions - sector, firm size, and region - so we can construct representative measures of technology for aggregates along these dimensions. Sampling weights are based on the inverse probability of selecting establishments within each stratum.

In these countries, we collected data for 3,996 establishments, including 711 establishments in the State of Ceará, in Brazil, 1,786 establishments in Senegal, and 1,499 establishments in Vietnam. These establishments were randomly selected based on the sampling frame of each country. Appendix A shows the distributions of the universe of firms (Tables A.1, A.3, and A.5) and the sample (Tables A.2, A.4, and A.6).[19]

[17]For the state of Ceará, it is representative at the state-level.

[18]Appendix A provides more details on sampling frame (A.2), survey implementation and data collection (A.6), and sampling weight (A.4). For Senegal and Vietnam, sampling uses the most recent census data from their respective national statistical office for sampling. For the state of Ceará in Brazil, sampling is based in the most recent census of employer-employee data from the Ministry of Economy, which provides annually updated information for every establishment. In Vietnam and Brazil, the sampling frame includes all formally registered businesses, while in Senegal it also includes establishments that have a business address premise regardless of whether they are classified as formal. The NSO in Senegal requires formal firms to use a harmonized accounting system in addition to being registered (ILO, 2020). These requirements are more stringent than those in Brazil and Vietnam where a registration suffices for a firm to become formal. As a result, many informal firms in Senegal would be classified as formal in the other two countries. In section G.3 of the appendix we show that our results are robust to restricting the Senegal sample to only formally registered firms.

[19]The average cost per survey was USD 82, varying between USD 68 and USD 95 across countries.

To ensure comparability, we implemented a standardized data collection protocol across all countries. The survey was implemented through face-to-face interviews by professional institutions and firms with knowledge and experience on data collection in each country. In Vietnam, the survey was implemented by the General Statistics Office (GSO) of Vietnam. In Ceará-Brazil, data collection was implemented by the State Industry Association (FIEC). In Senegal, data collection was implemented by Kantar-public. We followed the same protocols, translated in a standard "Terms of Reference" for implementation. For each country, there was a professional translation of each survey item from English to the local language and back again with interactions and revisions from World Bank team members supporting the implementation who are fluent in the original language and native speakers in the local language.

2.5 Design and implementation measures to minimize bias and measurement error

The literature on survey design has identified three types of potential bias and measurement errors based on whether they originate from the non-response, the enumerator, and the respondent (Collins, 2003). In what follows we describe the steps taken in the design and implementation of the FAT survey to minimize these errors.

Non-response bias. To maximize the response rate and minimize potential biases associated with non-response, due to lack of participation or lack of response to a particular question (Gary, 2007), we follow three steps. First, we partner with national statistical offices and industry associations to use the most comprehensive and updated sampling frame available, as well as their experience on data collection, which are supported by endorsement letters from local institutions.[20] Second, we follow a standard protocol in which each firm is contacted several times to schedule an interview. We split the sample in different batches, following the order of randomization within stratum, and provide contact information of subsequent batches only after interviewers have shown evidence that they have exhausted the number of attempts to complete the initial list. Third, we monitor the implementation, validation of skip conditions and outliers (e.g. balance sheet information) in real time, and request that any missing information are completed through a follow up call, checked by supervisors.

Enumerator bias and error counts. The survey, training, and data collection processes are largely designed to minimize enumerator biases and data collection errors. First,

[20] These procedures are in line with suggestions of good practice for implementation by Bloom et al. (2016).

the use of closed-ended questions makes coding the answers a mechanical task, eliminating the reliance on the enumerator's interpretation of the answer and subjective judgement to code them, as it is the case with open-ended questions (Bloom et al., 2016). Second, the same standardized training is implemented in each country with enumerators, supervisors, and managers leading the data implementation. Trainings are conducted by the team members who created the questionnaire, and in local languages - French, Portuguese and Vietnamese,[21] and they include vignettes to ensure that enumerators understand the specific technologies they are asking about. Third, in each country, we conduct a pre-test pilot of the questionnaire with firms out of the sample to ensure that interviewers clearly understand the questionnaire, that data collection is smooth, and that the enumerators training is sufficient. Fourth, to attain greater quality control during the data collection process, enumerators record the answers via *Computer-Assisted Personal Interviews* (CAPI) software.[22] One advantage of CAPI is that it allows the use of logical conditions which prevent some data inputting errors. Supervisors are assigned to review all interviews, identifying missing values and abnormal responses. The CAPI system identifies when enumerators complete the survey too fast or other abnormal issues that can raise concerns about the quality of the interview. Additionally, we regularly monitor the data collection process using standard algorithms to analyze the consistency of the data and provided continuous feedback to assure quality control.

Respondent bias. Two broad groups of factors can trigger response errors, *cognitive*, which affect the comprehension of the questions, and *framing*, which may cause biased answers due to the perceived socially (un)desirability of the answers (Bertrand and Mullainathan, 2001). We take several steps to minimize respondent bias. First, during the implementation of the screening process we ensure that the interview is arranged with the appropriate person or persons (Bloom and Van Reenen, 2010). Senior managers (and in larger firms other managers such as plant managers) are asked to respond to the sections that cover the technologies used, and HR managers are asked to respond the questions on employment. Second, we use face-to-face interviews, which lead to higher response rates and lower respondent bias and measurement errors than phone and web-based interviews.[23]

[21] In the former with the use of translation services support.

[22] Randomized survey experiments with household survey has demonstrated that a large number of errors observed in *Pen-and-Paper Personal Interview* (PAPI) data can be avoided in CAPI (Caeyers, Chalmers and De Weerdt, 2012).

[23] For example, Holbrook, Green and Krosnick (2003) use data from three experiments in the US and show that telephone respondents are less likely to cooperate and more likely to present themselves in socially desirable ways. Jackle, Roberts and Lynn (2006) show, in a experiment designed to evaluate the differences between the two modes of data collection, that telephone respondents are more likely to give socially desirable responses, which in our context is likely to result in an upward bias of technology use.

Third, the use of a closed-ended design in the questionnaire reduces measurement error in the answers as the respondent is questioned about specific technologies (one at a time), and only when the presence of each of the possible technologies is established, is she asked about the most widely used technology. Fourth, we pre-test the questionnaire in each country to ensure that questions are clear in their wording in the specific geographical and cultural contexts, simple, and objective, so that the response does not require any subjective judgement (Bertrand and Mullainathan, 2001). Fifth, to avoid *social desirability bias*, by which respondents may overstate the use of more sophisticated technologies, the survey avoids the words "technology" and "sophistication" and employs more neutral terms such as "methods" and "processes". Sixth, the survey is administered so that the respondent does not know all the possible technologies in a business functions before asserting whether a technology is used in the firm.[24] Finally, enumerators are instructed to visually verify the information provided during the interviews when possible.

2.6 Ex-post checks and validation exercises

We gauge the effectiveness of these efforts to minimize bias and measurement error by conducting several ex-post checks.

Non-response bias. The average (unit) response rate on the survey is 60 percent. By country, it is 80 percent in Vietnam, 57 percent in Senegal, and 39 percent in Ceará, Brazil.[25] These response rates are high relative to typical response rates in firm-level surveys, which for the U.S. are around 5 to 10 percent, and are consistent with response rates observed for WMS and MOPS (Bloom et al., 2016).[26] To minimize potential non-response bias, we adjusted the sampling weights for unit non-response. The non-response adjustment was calculated at the strata level, so that the weighted distribution of our respondent sample across strata (sector, size, region) exactly matches the distribution of establishments in the sampling frame.[27]

We conduct four tests to assess potential biases from cross-country differences in unit response-rates. First, using the information from the sampling frame, we check if there are differences in the average number of workers per firm between respondents and non-

[24] It also allows for "don't know" options.

[25] Within countries, there are no major differences across stratum, as described by Table A.8 in Appendix A. These are unweighted response rates calculated as the ratio between firms that responded the survey and the total number of firms in the sample which we attempted to conduct the interview. The high response rate for Vietnam is associated with the fact that the survey was implemented by the national statistical office.

[26] The average response rate for the WMS is around 40 percent.The response rate for MOPS, implemented by the United States Census Bureau, was around 80 percent.

[27] See section A.4 of the appendix for more details on sampling weights.

respondents within stratum. Second, under the premise that any systematic relationship between firm characteristics and participation is continuous in their reluctance to participate in the survey, we can learn about sample differences between respondents and non-respondents by comparing firms across different percentiles of the distribution of the number of attempts it took for them to respond the survey.[28] Using information on the number of attempts,[29] we compare the firm-level technology sophistication in GBFs, described in the next section, between firms with above and below the average number of attempts. Third, in a similar vein, we compare firms in the first list of contacts provided to interviewers, versus those provided subsequently. Fourth, for Brazil, we have access to a matched employer-employee administrative dataset with information on workers' characteristics for the full universe of firms used in the sampling frame. We compare five labor-related variables in the final weighted sample of FAT with our universe of firms in the State of Ceará.[30]

In each of these exercises, we find no statistical difference in the number of employees, technology sophistication, wages, and share of workers by skill and education between firms in the group that proxies for the response sample and the group of firms that proxies for the non-response sample.[31]

Enumerator bias. We study the possibility of biases induced by enumerators when administering the survey by studying the significance of enumerator dummy variables for average firm-level sophistication measures conditional on firm observable characteristics. In Ceará, none of the dummy coefficients are statistically significant, while in Senegal and Vietnam, only 9% and 8% of the coefficients are statistically significant (Table A.13 of the appendix). The average country-level technology sophistication computed after excluding enumerators with significant dummies is not statistically (or economically) different to the average technology sophistication in full sample (Table A.14 of the appendix).

Response bias. To assess the relevance of response bias, we conduct a parallel pilot in Kenya where we re-interview 100 randomly selected firms with a short version of the questionnaire. For those firms, we randomly select three business functions and ask about the presence of the relevant technologies.[32] Both the original and back-end interviews in the

[28] Behaghel et al. (2015) infer the reluctance to participate in the survey from the number of attempts that it take for a firm to accept the request.

[29] We collected the number of attempts it took for a firm to answer the survey for Senegal. On average, it took three attempts to complete the survey.

[30] The variables are number of workers, average wages, share of workers with college degree, share of low skilled, and share of high-skilled workers, where high- and low-skilled workers are defined as in David and Dorn (2013).

[31] See Table A.9 to A.12 in Appendix A.

[32] The pilot coincided with the beginning of the data collection for phase two which includes new countries, and Kenya is one of them. Despite the fact that Kenya is not in the sample, the pilot is informative about the significance of response bias. The re-interviews produce 1,661 answers (106 interviews times 3 business

pilot are conducted by phone by different interviewers.

Despite using phone interviews which are subject to greater measurement error than face-to-face interviews, comparison of answers from the pilot reveals that 73% of the answers were the same across the two interviews.[33] We estimate a probit model to assess the likelihood of consistent answers between the original and the back-check interviews, controlling for firm-level fixed-effect. Reporting the use of a technology in the back-check interview is associated with 80.6% of likelihood of reporting the use of the same technology in the original interview. Conversely, reporting that a technology is not used in the back-check interview, is associated with a 29.3% likelihood of being reported in the original survey.

In addition to this pilot, we have also checked the accuracy of the responses in the survey for Brazil by comparing the firm-level value added per worker constructed from answers about the firm value of sales, materials and number of workers in FAT, with measures of average wages obtained from the administrative matched employer-employee RAIS data.[34] Table A.15 of the appendix shows that average log of wages from RAIS are strongly correlated with the FAT measures of log value-added per worker. These ex-post tests validate the soundness of the survey design, data collection process and accuracy of responses.

3 Technology Sophistication Measures

We use the detailed information from FAT to construct cardinal measures of technology sophistication. Cardinalization of ordinal rankings is standard in economics as it facilitates algebraic manipulation and statistical analysis. In this section, we discuss how we demonstrate the robustness of our findings to alternative, plausible cardinalizations of the ordinal sophistication rankings. We further validate the technology sophistication measures by showing their correlation with off-the-shelf proxies of firm technology from FAT and RAIS, and conclude the section with a two-firm case study that illustrates the granularity of the characterization of the firm' technological landscape that our measures provide and motivates some of the key questions we explore in our analysis.

functions times an average of 5.2 technologies per function).

[33] The consistency ranges from 65% in business administration to 77% in sales across business functions, and from 85% among the most basic technologies to around 61% in intermediate, and 77% at the most advanced technologies across functions.

[34] The *Relação Anual de Informações Sociais* (RAIS) is an administrative database maintained by the Ministry of Labor providing information of salary for all formal workers in Brazil.

3.1 Baseline measures

Based on the experts' assessment, we order the technologies in each function f according to their sophistication, and assign each a rank $r_f \in 1, 2, ..., R_f$, from least to most advanced. Because several technologies may have the same sophistication, the highest rank in a function R_f may be smaller than the number of possible technologies N_f.[35] We define the relative rank of a technology as $\hat{r}_f = \frac{r_f - 1}{R_f - 1}$. Note that $\hat{r}_f \in [0, 1]$. The technology sophistication of business function f in firm j is a monotonic increasing function of the relative rank of *the most widely used technology* of firm j in function f ($\hat{r}_{f,j}$). For example, our baseline sophistication measure is

$$s_{f,j} = 1 + 4 * \hat{r}_{f,j}. \tag{1}$$

Because our baseline sophistication measure is linear, it displays constant increments in sophistication as we move up in the rank. A priori, the sophistication measures could also be concave or convex in the rank, reflecting diminishing or increasing marginal increments in sophistication as the rank increases. The non-uniqueness of latent cardinal variables associated with an ordinal rank such as $\hat{r}_f$ is common in many economic applications such as measures of institutional quality, quality of education, well-being, trust, social norms, and sophistication of management practices, to name a few. However, it is critical that researchers demonstrate that the conclusions from their analysis are robust to alternative plausible cardinalizations of the ordinal rankings they measure. Next, we discuss how we ensure that this is the case for each of the various questions we explore.[36]

3.2 Robustness to cardinalization

First order stochastic dominance. As we show in section 4.2, the cross-firm distribution of technology sophistication (both at business function and firm levels) have (restricted) FOSD when comparing bilaterally the countries in our sample. Given two distributions of an ordinal variable, if one first-order stochastic dominates (FOSD) the other, then population means comparisons are robust to the cardinalizations of the ordinal variable.[37] Therefore, cross-country comparisons of average firm or business-function sophistication are robust to

[35] 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.

[36] We present additional robustness checks for our measures of technology sophistication in Appendix B. Section G.1 of the Appendix shows that our results are robust for alternative cardinalization parameters for sophistication rankings.

[37] See Lehmann (1955), Hadar and Russell (1969) and Hanoch and Levy (1969).

arbitrary (monotonically increasing) cardinalizations of the technology rankings.

LMA curves. Schroeder and Yitzhaki (2017) have shown that a sufficient condition for the robustness to cardinalization of the association between a variable and the cardinalized ordinal variable is that the LMA curve (line of independence minus absolute concentration curve) does not cross the horizontal axis.[38] When exploring the association of sophistication and firm characteristics, we check that the LMA condition holds, and, therefore, the sign of their association is robust to using alternative cardinalizations of the sophistication rankings. Section B.1 of the appendix reports the results of LMA curves we estimated.

Plausible cardinalizations. The LMA test is only valid for univariate regression analysis and is uninformative about the robustness of magnitudes. To overcome these limitations, Bloem (2019) proposes a methodology which consists in (i) specifying a general class of parameterizations of the ordinal measures, (ii) defining the subgroup of plausible parameterizations within the class, and (iii) exploring the robustness of the findings to the subclass of plausible parameterizations of the latent variable. We implement Bloem's methodology by adopting the following class of technology sophistications measures

$$s^{\phi}_{f,j} = 1 + 4 * \hat{r}^{\phi}_{f,j}, \tag{2}$$

where the parameter $\phi > 0$ governs the curvature of the mapping from technology ranks to sophistication measures.

To narrow down the range of plausible values for ϕ, we anchor technology sophistication in firm-level productivity (log value added per worker).[39] This means that we set the measures of firm sophistication for various values of ϕ on an interpretable metric by projecting firm productivity into the sophistication measures, and then we deem plausible the values of ϕ for which the skewness of the cross-firm distribution of projected productivity are close to the observed skewness of the cross-firm distribution of productivity.[40]

[38]The LMA curve is the vertical difference between two curves. The first curve is the absolute concentration curve of a variable X (e.g., firm size) given the technology sophistication $s_j$under the assumption that the two variables are statistically independent. The second curve is the absolute concentration curve of X as a function of the cumulative distribution $F(s_j)$.

[39]Prior examples of setting an ordinal variable in an interpretable metric by anchoring it in an observed cardinal variable include Cawley, Heckman and Vytlacil (1999), Cunha and Heckman (2007) and Cunha, Heckman and Schennach (2010), who anchor test scores in future earnings, and discuss alternative anchoring variables such as high school graduation rates, college enrollment.

[40]Average firm sophistication is constructed as the simple mean of the sophistication across the business functions of a firm ($s^{\phi}_{f,j}$). In conducting this comparison, we first regress log productivity and firm sophistication on a set of firm-level controls that include dummies for country, sector, size, age, exporter and multinational status.

Table B.1 of the appendix reports the skewness of the cross-firm distribution of productivity (row 1), and of the distributions of projected productivity on firm sophistication for different values of ϕ. The skewness of the projections of firm productivity on sophistication vary significantly with ϕ, with small negative skewness for low values of ϕ and large positive skewness levels for high values of ϕ. The skewness of the distribution of productivity is 0.27, which falls in between the skewness of the projection on sophistication when using a value for ϕ of 2/3 (0.18) and 1 -our baseline- (0.41). Therefore, a plausible range for ϕ is between 2/3 and 1.

In section G.1 of the appendix, we explore the robustness of our findings to more values for ϕ that range from 1/3 to 3. These values are quite extreme as they imply relative increases in sophistication (and productivity) across ranks that are implausible.[41] Our results are robust to using these implausible cardinalizations of the sophistication rankings.

3.3 Correlation with off-the-shelf proxies

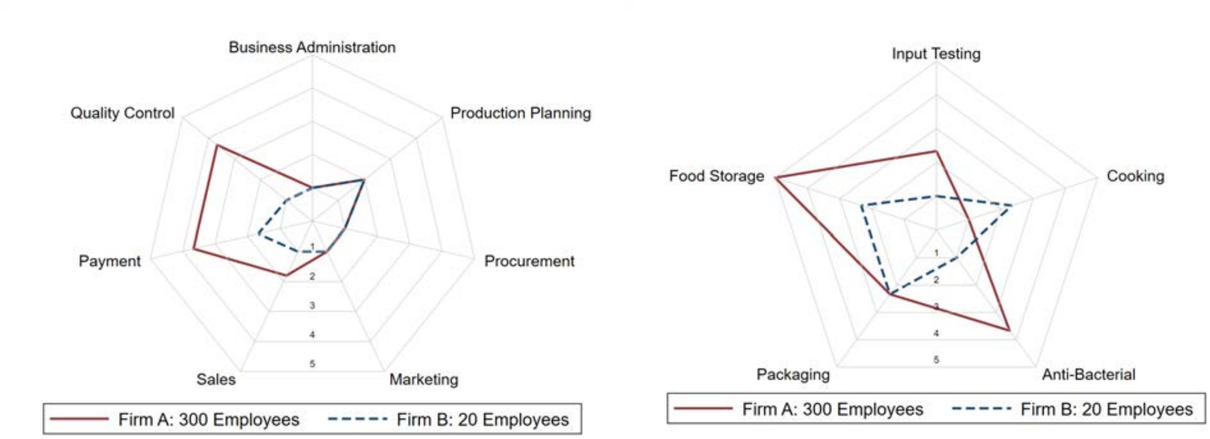
We conduct an additional validation of the sophistication measures by computing the correlation with off-the-shelf variables that indirectly proxy for the use of advanced technologies. These include firm size (measured by the number of workers), exporter and multinational status, various measures of the occupation composition of the firm's labor force (percent of professional, managers, and technicians), its education and human capital (percent with college degrees, percent with engineering and post-graduate studies, average wages),[42] and whether the company conducts R&D. In all cases, we control for the country and sector of a firm by first partialing out country and sector dummies from all variables. Table B.2 of the appendix reports the partial correlations. As expected, there is a positive, statistically significant association between average firm-level sophistication and all the indirect proxies for firm-level technology we consider.

[41]To illustrate this point, consider values of $\phi \in 1/3, 3$, and a business function with five ranks (i.e. $R_f = 5$). When $\phi = 1/3$, the increment in sophistication when we move from the first to the second rank is 2.52, while the increment when we go from the fourth to the fifth is almost seven times smaller (0.36). In contrast, when $\phi = 3$ the increment in sophistication when moving from the fourth to the fifth rank is 2.3 which is 37 times larger than the increment when going from the first to the second rank. These relative increases in sophistication are implausible as our sector and technology experts have reassured us that increases in ranks within any given business functions are associated with significantly greater levels of sophistication, but that the output productivity or cost reductions associated with them are never greater than a factor of 2.

[42]We have two sources for average wages. In FAT we collect data on total wages and number of employees. Additionally, for Brazil, we have average wages for the interviewed firms from RAIS.

3.4 A case study

We illustrate the granularity of the technology sophistication information in FAT by studying two Senegalese firms in the food processing sector. Firm A has 300 employees while firm B has 20. Figure 3 presents in two spider charts the sophistication of the most widely used technology ($s_{f,j}$) in each of 12 business functions (seven GBFs in the left chart and five SSBFs in the right) in each firm (A in solid red, and B in dashed blue). Figure 3 provides a rich description of the technological landscape in firms A and B which can be used to compare the sophistication of technology across firms but also across the business functions of each individual firm.



(a) General business function

(b) Sector-specific business function

Figure 3: Example of Two Firms in Food Processing in Senegal

Note: Two firms in Food Processing in Senegal are selected to provide an example of the technology sophistication. The sizes of Firm A and B are 300 and 20 employees, respectively.

Firm A has greater average sophistication than firm B (2.3 vs. 1.4). This is the case both in GBFs and in SSBFs, with a similar gap in average sophistication in both classes of business functions.[43]

Figure 3 allows us to explore the variation in sophistication across the business functions of a firm. Take for example firm A. In some business functions such as marketing and business administration, firm A uses the least sophisticated technologies available, while in others such as food storage payments or quality control it employs technologies that are close to the most sophisticated technologies available. In contrast, firm B has a more uniform sophistication across business functions.[44]

[43] $2.6 - 1.7 = 0.9$ in SSBFs and $2 - 1.2 = 0.8$ in GBFs.

[44] The variance in sophistication across the business functions is 1.8 for firm A and 0.36 for firm B. The definition of within-firm variance we introduce below nets out a business function fixed effect that removes the mean sophistication in each business function across firms.

These observations motivate some of the key questions we explore in the paper. First, is the wide variation in sophistication across functions that we observe in firm A common in the data or is it an anomaly? Second, which firms have greater variance in sophistication across business functions? Is greater within-firm variance in sophistication driven by firm size, by average firm-level technology sophistication, or by other observable characteristics? Third, in what business functions is there greater cross-firm variance in technology sophistication? Finally, is there a statistical association between firm-level productivity and average firm sophistication or between firm productivity and variance in technology sophistication across business functions of a firm? What mechanisms may cause these associations?

4 Cross-Firm Technology Facts

We divide our analysis of the FAT technology measures in two parts. In this section, we focus on cross-firm differences in technology sophistication and in section 5 we explore the differences in technology sophistication across business functions, within the firm.

To study technology across firms, we start by constructing measures of the average sophistication of technology at the firm level as simple averages of technology sophistication across all business functions, (ABF), only across general business functions (GBF), and only across sector-specific business functions (SSBF). With these measures, we explore the existence of cross-country and cross-regional differences in technology sophistication, whether these vary across sectors, the distribution of technology sophistication across firms, and the relationship between firm-level technology and observable characteristics.[45]

4.1 Aggregate differences in technology sophistication

Countries Our exploration of technology sophistication starts by revisiting the well-established fact that technology varies significantly across countries (Comin and Hobijn, 2010; Comin and Mestieri, 2018). Table 1 presents country-level sophistication (S_c) constructed as the average of sophistication across the firms in the country.[46] For all three broad classes of

[45] Appendix C provides additional descriptive statistics and tests showing that results presented in this section are robust if the exercises are conducted for specific sectors. Regarding sector heterogeneity, the firms in FAT belong to 227 different 4-digit sectors, following the International Standard Industrial Classification of all Economic Activities (ISIC). To ensure that the variation in technology sophistication and that associations between sophistication and firm characteristics/productivity are not driven by sectoral heterogeneity, section G.2 of the appendix reports the robustness of all cross-firm results to controlling for 4-digit sector effects. Within-firm facts are unaffected by sectoral heterogeneity as we remove a firm-level fix effect prior to computing within-firm variance in sophistication

[46] As with the sectoral or regional counterparts, we just use sampling weights to ensure the representativeness of the statistic.

business functions (ABF, GBF and SSBF), we observe that the country rankings based on S_c and per capita income coincide. Cross-country differences in S_c are significant. Relative to the maximum possible distance – the difference between the upper and lower limits of the range of the sophistication indices (i.e., $5 - 1$) – the difference between Brazil and Senegal in S_c is 25% for ABFs, 30% for GBFs and 16% for SSBFs.

Table 1: Average Technology Sophistication by Country and Type of Business Function

	ABF	GBF	SSBF
Overall	1.85	1.90	1.66
Brazil (BR)	2.32	2.49	1.92
Vietnam (VT)	1.91	1.92	1.80
Senegal (SN)	1.31	1.29	1.27
Gap: BR - SN	1.01	1.20	0.65
Relative Gap	25%	30%	16%

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

Table 2: Cross-Country Average Technology Sophistication by Sector

	ABF			GBF			SSBF		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.93	1.75	1.89	1.76	1.76	1.97	2.17	1.61	1.68
Brazil (BR)	2.52	2.12	2.38	2.32	2.16	2.60	2.81	1.92	1.89
Vietnam (VT)	2.02	1.86	1.92	1.79	1.89	1.93	2.32	1.64	1.89
Senegal (SN)	1.25	1.26	1.36	1.16	1.23	1.38	1.39	1.26	1.25
Gap: BR - SN	1.27	0.86	1.02	1.16	0.93	1.22	1.42	0.66	0.64
Relative Gap	32%	22%	26%	29%	23%	31%	36%	17%	16%

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. Overall is the average of Brazil, Vietnam, and Senegal. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 ($(Brazil - Senegal)/Maximum\ Gap\ (4)$). Technology measures are weighted by the sampling weights.

Sectors Next, we study the presence of systematic differences in technology sophistication across sectors. Table 2 presents the average technology sophistication in each sector (S_s). The first row reports the values of S_s for the full sample. Average technology sophistication differs across sectors. For GBFs, S_s is highest in services, suggesting that GBFs are more central for the production of services than in manufacturing or agriculture. In SSBFs, S_s is highest in agriculture. Of course, comparisons of SSBFs sophistication levels across sectors are affected by the cross-sectoral differences in the technology grids.

Rows 2-4 of Table 2 report average sectoral sophistication by country ($S_{c,s}$). In all sectors and types of business functions, the ordering of countries by $S_{c,s}$ coincides with the ordering by income per capita. Cross-country differences in $S_{c,s}$ vary significantly across sectors. For GBFs, the gap in $S_{c,s}$ between Brazil and Senegal is largest in services, while in SSBFs the Brazil-Senegal gap in $S_{c,s}$ is twice as large in agriculture than in the other sectors. When considering all business functions (ABF), the cross-country average sophistication gap is also largest in agriculture, followed by services and it is smallest in manufacturing.[47] This sectoral variation in the cross-country technology gap is reminiscent of the fact documented by Caselli (2005) that the productivity gap between rich and poor countries is much larger in agriculture than in non-agricultural sectors. Table 2 provides another possible explanation of this puzzle. Namely, that the larger agricultural productivity gap is (partly) due to the larger differences in the technological sophistication of production processes between rich and poor countries that we observe in agricultural firms.[48]

Regions We explore further the cross-sectional relationship between technology sophistication and development by zooming into the 16 regions that make up our sample. We construct regional measures of technology sophistication (S_r and $S_{r,s}$) and productivity as the weighted average of firm-level variables.[49] Figure 4 presents the scatter plot of regional technology sophistication against regional productivity. The correlation between these two variables is 0.93, consistent with the cross-country association between technology sophistication and productivity. Table C.2 of the appendix explores the presence of sectoral differences in sophistication across regions. As with the country aggregates, the table confirms that the gap in technology sophistication between the richest and poorest regions in our sample is largest in agriculture and smallest in manufacturing for ABFs and SSBFs, while for GBFs it is largest in services.

[47] Note that these patterns imply that, there are greater cross-country differences in sophistication (i.e., $S_{BRA,s} - S_{SEN,s}$) in sectors/business functions classes where average sophistication (S_s) is greater.

[48] Table C.4 in Appendix C focuses on the four sectors where we have the largest number of observations to explore the robustness of these patterns to controlling for variation in the sectoral composition of manufacturing, services and agriculture. The four sectors considered are crops (in agriculture), food processing and apparel (in manufacturing) and wholesale and retail trade (in services). The key finding is that all the sectoral patterns documented in Table 2 are robust to controlling for the composition of the broad sectors.

[49] See the Appendix C.2 for details.

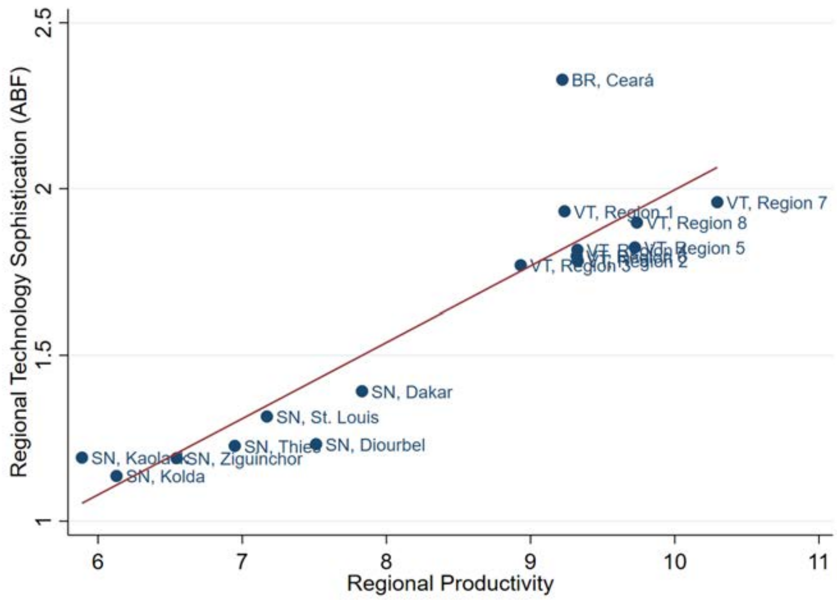


Figure 4: Region-level Technology Sophistication vs. Regional Productivity

Note: The regional average of technology sophistication (ABF) is on the y-axis. The regional productivity is on the x-axis. The regional productivity is measured as the average value added per worker based on a representative sample of the FAT data for each region. BR, VT, and SN are Brazil, Vietnam, and Senegal, respectively. Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh).

4.2 Distribution of firm-level sophistication

An important advantage of a firm-level dataset such as FAT is that we can go beyond comparing average sophistication across countries or regions and characterize the entire distribution of technology sophistication across firms. Figure 5 plots the kernel density of the distribution of the firm-level sophistication, s_j, in each of the three countries.[50] Visual inspection of the densities suggests the possibility of first order stochastic dominance. We conduct the Kolmogorov-Smirnov-based tests introduced in Goldman and Kaplan (2018), of the null hypothesis of equivalence of all cumulative density function (CDF) values between two distributions.[51] The tests confirm that the cross-firm distribution of s_j in Brazil first

[50]We conduct Kolmogorov-Smirnov (KS) tests with the null that the distributions of s_j are (pairwise) equal across countries. We reject the equivalence of all the pairwise distributions, which confirms that the distribution of s_j is different across all three countries.

[51]We use the STATA discomp package developed in Kaplan (2019). To avoid the "multiple testing problem" that increases the Type I error (α), the KS-based multiple test uses "familywise error rate" (FWER) that provides the probability of rejecting at least one true null hypothesis. Figure C.1 in the appendix shows the pairwise comparisons of CDFs and the results of the KS-based multiple test for each value.

order stochastic dominates in a restricted sense[52] the distribution of Vietnam for most of the domain of the technology indices, which in turn also first-order stochastic dominates in a restricted sense the distribution of s_j in Senegal.[53]

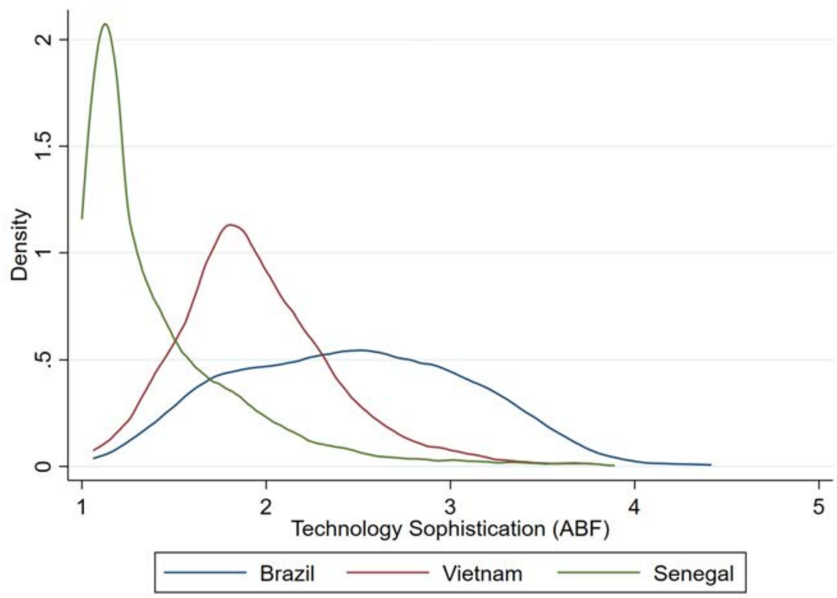


Figure 5: Distribution of Technology Sophistication (s_j)

4.3 Cross-firm variance in sophistication

If technology sophistication is a driver of cross-firm productivity variation, then it is important to understand how sophistication varies across firms. To this end, consider the following decomposition of firm sophistication (s_j), where S is the average sophistication in the sample, and S_c is the average sophistication in country c:

$$s_j - S = \overbrace{s_j - S_c}^{Within} + \overbrace{S_c - S}^{Between} \tag{3}$$

[52] See Atkinson (1987)

[53] Specifically for the comparison Brazil-Vietnam, we find stochastic dominance for the domain of the distribution of s_j between [1.74, 4.70], which includes 97% of Ceará firms and 96% of Senegal firms. For the pair of distributions Brazil-Senegal we reject the test of equality for the domain of s_j [1.10, 4.70], which includes 98% of the firms in both countries' samples; and for Vietnam-Senegal the domain of s_j where we reject equality of the distributions is [1.08, 3.97] that include 95% and 97% of firms in the sample respectively. The test is also rejected for some values above that range, but not for others.

Using identity (3), we decompose the variance of firm-level sophistication into a within-country component that captures the variance in sophistication across the firms in a country[54] and a between-country component that captures the variance in the average (country-level) sophistication across the three countries. Table 3 reports the between (row 1) and within (row 2) variances. Row 6 presents the contribution of the within-country component to the total variance across firms in technology sophistication. For all three groups of business functions, the within-country component accounts for a majority of the cross-firm variance in technology sophistication. In particular, it accounts for 54% of the variance of firm-level sophistication of ABFs, for 50% of GBFs and for 76% of SSBFs.[55]

Next, we study how within-country variance in firm sophistication varies across countries. Rows 3-5 of Table 3 report the variance of firm-level technology sophistication (s_j) in each country. For all three groups of business functions, we find greater cross-firm dispersion in firm sophistication in Brazil. For GBF and ABF the cross-firm variance is similar in Vietnam and in Senegal, but for SSBF it is greater in Vietnam.[56] Figure 5 and Table 3 suggest the existence of a positive association between cross-firm dispersion in technology sophistication and development. To further explore this hypothesis, we turn to our regional disaggregation and plot in Figure 6 the cross-firm variance in technology sophistication in each region against the regional productivity level. The figure confirms the strong association between the two variables with a correlation of 0.83.

4.4 Role of observable characteristics

So far we have characterized different aspects of the distribution of firm-level technology sophistication. Next, we explore the association between technology sophistication and firm-level observable characteristics. The list of variables we consider includes firm size (5-19, 20-99, 100+ employees), sector (agriculture, manufacturing and services), age (0-5, 6-10, 11-15, and 16+ years), export and foreign ownership status. To study their association with sophistication, we regress s_j on country dummies and the full set of dummies that capture the firm observable characteristics. Table 4 reports the estimates. Controlling for other observables, technology sophistication increases with firm size, it is higher in foreign owned

[54] We compute the variance of the within term in row 2 as the simple mean of the variance of the within term in the three countries.

[55] The relative contributions of the cross-firm/cross-country components is not due to the fact that we only have three countries in the sample. We obtain similar results in a within-between decomposition with our 16 regions, as reported in Table C.2. The cross-firm/cross-country component is not driven by sectoral compositions either. Although there are some variations, we found consistent cross-country gap

[56] The relative contributions of the cross-firm/cross-country components is not due to the fact that we only have three countries in the sample. We obtain similar results in a within-between decomposition with our 16 regions, as reported in Table C.3.

Table 3: Cross-Firm Variance in Technology Sophistication

	ABF	GBF	SSBF
$Var(S_c - S)$	0.18	0.25	0.08
$Var(s_j - S_c)$	0.20	0.25	0.26
$Var(s_{j,Brazil} - S_{Brazil})$	0.36	0.48	0.38
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.13	0.14	0.25
$Var(s_{j,Senegal} - S_{Senegal})$	0.12	0.13	0.17
Contribution within	0.54	0.50	0.76
Contribution within with controls	0.46	0.43	0.71

Note: Technology measures are weighted by the sampling weights. Contribution within with controls is estimated after controlling for size group small, medium and large), sector (agriculture, manufacturing and services), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status.

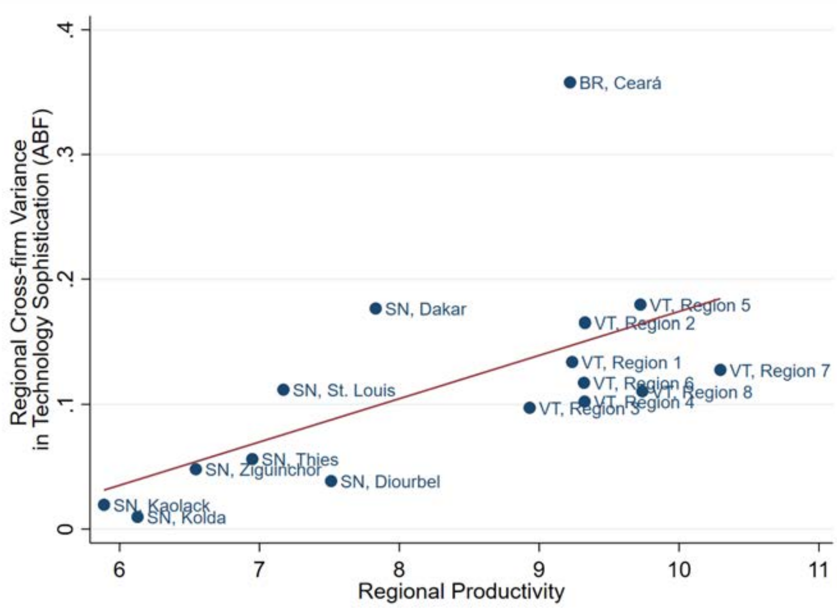


Figure 6: Cross-Firm Variance of Technology Sophistication vs. Regional Productivity

Note: The regional level cross firm variance of technology sophistication (ABF) is on the y-axis. The regional productivity is on the x-axis. The regional productivity is measured as the average value added per worker based on a representative sample of the FAT data for each region. BR, VT, and SN are Brazil, Vietnam, and Senegal, respectively. Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh).

firms and in exporters. However, technology sophistication does not systematically vary with firm age. These associations are robust across all three business function groupings. We also explore whether the association of sophistication and observable characteristics varies across the three broad sectors. (See Table C.9 to C.11 in Appendix C.) The main finding is that qualitatively the patterns reported in Table 4 also hold across sectors. However, the point estimates vary across sectors. Increases in firm size are associated with greater increases in the sophistication of ABF and GBF in manufacturing and services than in agriculture, and with greater increases in the sophistication of SSBFs in firms in the service sector. Conversely, exporter status and foreign ownership are associated with greater sophistication of ABFs and GBFs in agriculture than in manufacturing and services.

We use the estimates from Table 4 to revisit the within-between decomposition from the previous subsection and study how much the contribution of the within-country component to the variance in firm-level sophistication changes once we filter out firm-level observable characteristics. The last row of Table 3 shows that the majority of the cross-firm variance in sophistication is not accounted for by our list of firm observable characteristics, and that after taking those into account, the within component represents between 43% and 72% of the variance in firm-level sophistication.

5 Technology within Firms

The granularity of the information collected in the FAT survey offers a unique opportunity to study technology inside firms. From a research standpoint, this is largely uncharted territory. Previous references in the literature to variation in technology inside firms exploited the multi-plant nature of firm (e.g., Fort, Pierce and Schott, 2018). In FAT the sampling unit is the establishment. Therefore, our notion of variation in technology within firms refers to differences in the sophistication of the technologies used across the different business functions of *one* establishment.

In this section, we explore three issues. First, we study the magnitude of within-firm variance in sophistication, especially relative to the variance in sophistication across firms. Second, whether within-firm variance correlates with firm characteristics such as average firm-level sophistication and firm size. Third, what are the sources of variation in technology sophistication across the business functions of a firm.

5.1 Within-firm variance in technology

To quantify the within-firm variance in technology, we decompose technology sophistication at the firm-business function level ($s_{f,j}$) between a firm component (α_j), a business function-country component ($\beta_{f,c}$), and a residual ($u_{f,j}$):

$$s_{f,j} = \alpha_j + \beta_{f,c} + u_{f,j}, \tag{4}$$

Table 4: Technology Sophistication and Firm Characteristics

	s_j		
VARIABLES	ABF	GBF	SSBF
Vietnam	-0.41***	-0.56***	-0.11***
	(0.02)	(0.02)	(0.02)
Senegal	-0.94***	-1.08***	-0.62***
	(0.02)	(0.02)	(0.02)
Manufacturing	-0.08**	0.04	-0.36***
	(0.04)	(0.04)	(0.04)
Services	0.05	0.30***	-0.26***
	(0.04)	(0.04)	(0.04)
Medium	0.20***	0.23***	0.09***
	(0.02)	(0.02)	(0.02)
Large	0.53***	0.59***	0.32***
	(0.03)	(0.03)	(0.04)
Age 6 to 10	-0.02	-0.03	0.00
	(0.02)	(0.02)	(0.03)
Age 11 to 15	-0.02	-0.01	-0.00
	(0.02)	(0.02)	(0.03)
Age 16+	0.02	0.03	0.01
	(0.02)	(0.02)	(0.03)
Foreign Owned	0.25***	0.27***	0.22***
	(0.03)	(0.03)	(0.05)
Exporter	0.13***	0.12***	0.10***
	(0.02)	(0.02)	(0.03)
Observations	3,896	3,896	3,076
R^2	0.55	0.57	0.29

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

We define the within-firm variance in technology sophistication for firm j ($WVar_j$) as the variance across the business functions of firm j of $u_{f,j}$. The business functions dummies in equation (4) absorb variation in $s_{f,j}$ driven by the nature of business functions in a firm. By purging this component, the variance of the residuals is comparable across firms with potentially different business functions (as they may have different SSBFs).

Table 5 reports the average within-firm variance (row 1). For comparison purposes, we also report the cross-firm variance in technology (row 2). Columns 2-4 report these statistics for each of the three countries, and column 1 reports the average of columns 2-4. The main finding, and one of the most surprising in the paper, is that the within-firm variance in technology is (on average) 2.8 times larger than the cross-firm variance in technology sophistication. This finding debunks the notion that technology sophistication is relatively uniform within firms. Furthermore, together with the evidence from section 4.3, this fact implies that, as we reduce the level of aggregation (i.e., from the country to the firm, and from the firm to the business function), the (within) variance in technology sophistication across units increases.

Within-firm variance and aggregate development The rest of this section investigates the sources of within-firm variance in sophistication. Our first step is to explore how does within-firm variance in sophistication differ across countries. Table 5 shows that the average within-firm variance in sophistication is highest in Brazil and it is lowest in Senegal.

Table 5: Within-firm Variance in Technology Sophistication

	All	Brazil	Vietnam	Senegal
$Var(s_{f,j} - s_f - s_j)$	0.56	0.93	0.48	0.26
$Var(s_j - S_c)$	0.20	0.36	0.13	0.12

Note: Estimates are weighted by the sampling weights.

We explore further the relationship between within-firm variance and development by zooming into the regions. Figure 7 plots the average within-firm variance in each of the 16 regions against the log of regional productivity. The correlation coefficient between these two variables is 0.66.

Firm characteristics To study the relationship between within-firm variance ($WVar_j$), firm sophistication, s_j, and other characteristics, X_j, we estimate

$$WVar_j = \alpha_c + \beta s_j + \gamma X_j + u_j \tag{5}$$

Table 6 reports the estimates.[57] We find that the within-firm variance in technology is strongly associated with firm-level sophistication (s_j). The relationship is positive and concave. Conditional on s_j and the country dummies, the coefficients for the other firm-level characteristics such as firm size, age , sector and multinational status are largely insignificant. Exporter status and the age dummy for firms between 6 and 10 years old are both positively associated with within-firm variance.

[57] In Appendix E, we show that the estimates are robust to replacing the categorical dummies for age and size by the continuous variables (Table E.1). We also show the robustness of the estimates to controlling for the number of business functions (Table E.2) and including four-digit SIC dummies (Table G.23).

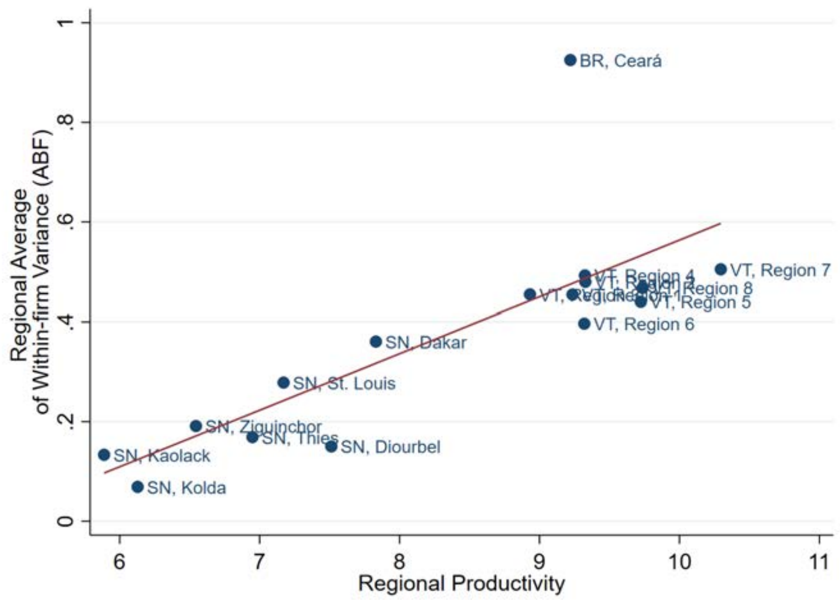


Figure 7: Within-Firm Variance of Technology Sophistication vs. Regional Productivity

Note: The regional average of within firm variance of the ABF is on the y-axis. The regional productivity is on the x-axis. The regional productivity is measured as the average value added per worker based on a representative sample of the FAT data for each region. BR, VT, and SN are Brazil, Vietnam, and Senegal, respectively. Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh).

5.2 Sources of within-firm variance in technology sophistication

The magnitude of the within-firm variance in sophistication refutes the notion that technology is uniform within firms and poses a new question about the source of disparity in technology sophistication across the business functions of a firm. To explore this question, we develop a model that formalizes the technology adoption decisions of a firm. We then study the implications of optimal technology choices for the drivers of within-firm variance in technology sophistication.

The technology index

We start by introducing a firm-level technology index, a_j, that aggregates of the vector of sophistication levels across the business functions ($\{s_{f,j}\}_{f\in\mathcal{F}_|}$),[58] and that is sufficient statistic for the effect that technology sophistication has on firm output and revenue. The technology

[58] Where $\mathcal{F}_|$ is the set of business functions in firm j.

Table 6: Within-Firm Variance in Technology Sophistication and Firm Characteristics

VARIABLES	$WVar_j$
s_j	1.49***
	(0.07)
s_j^2	-0.26***
	(0.02)
Vietnam	-0.36***
	(0.02)
Senegal	-0.18***
	(0.02)
Manufacturing	0.02
	(0.04)
Services	0.03
	(0.03)
Medium	-0.02
	(0.02)
Large	0.04
	(0.03)
Age 6 to 10	0.05**
	(0.02)
Age 11 to 15	-0.01
	(0.02)
Age 16+	0.02
	(0.02)
Foreign owned	0.03
	(0.03)
Exporter	0.04**
	(0.02)
Observations	3,893
R^2	0.44

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

index is implicitly defined by the following non-homothetic CES aggregator of $(\{s_{f,j}\}_{f\in\mathcal{F}_|})$:[59]

$$\sum_{f=1}^{N_f}\left(\Omega_f^{\frac{1}{\sigma}}e^{\frac{\varepsilon_f a_j}{\sigma}}\right)e^{\frac{\sigma-1}{\sigma}s_{f,j}}=1 \tag{6}$$

$\sigma\in(0,1)\cup(1,\infty)$ is the elasticity of substitution between sophistication across business functions, $\Omega_f>0$ (with $\sum_{f=1}^{N_f}\Omega_f=1$) is a parameter that affects the importance of business function f for the technology index, and $\varepsilon_f(>0)$ is a parameter that captures the elasticity of the sophistication in a business function $(s_{f,j})$ with respect to the firm-level technology

[59] Hanoch (1975) introduces this formulation to study consumer choices. Comin, Lashkari and Mestieri (2021) embed Hanoch's formulation in a dynamic general equilibrium setting to study structural transformations. We use the nh-CES formulation to study the technology side of the firm.

index (a_j). If $\varepsilon_f = 1 - \sigma, \forall f$, (6) becomes the standard homothetic CES aggregator.

Appendix D shows that, to a first order, a_j is equal to

$$a_j \simeq \alpha + \beta(s_j + \gamma_j \sqrt{WVar_j}) \tag{7}$$

where α and $\beta = \frac{(1-\sigma)}{\bar{\varepsilon}}$ are constants, where $\bar{\varepsilon} = \sum_f \omega_f \varepsilon_f$ is the weighted average of ε_f, with the same weights ω_f across firms.[60] γ_j is a firm-specific parameter that reflects the cross-function correlation between $s_{f,j}$ and ω_f.

Intuitively, the technology index is increasing in the average sophistication of the firm, s_j. Conditional on the average sophistication, a_j is higher in firms that allocate more sophisticated technologies to functions that are more important. This wedge between the technology index and average sophistication reflects the covariance between $s_{f,j}$ and the function weight ω_f. This covariance can be expressed as the product of the correlation between $s_{f,j}$ and the function weight ω_f, the standard deviation of the function weight, and the within-firm dispersion in sophistication, $\sqrt{WVar_j}$.[61] If the correlation between $s_{f,j}$ and the function weight ω_f is positive, the wedge is increasing in the within firm variance ($WVar_j$).

Optimal technology sophistication

Consider a firm whose operating profits $\Pi_j(a_j)$ are increasing and concave in the technology index, a_j. Firms incur a cost $C_{fj}(s_{f,j}) = C_j C_{f,X} e^{s_{f,j}}$ of making a technology with sophistication $s_{f,j}$ the most widely used in business function f. This cost of adoption is increasing and convex in the sophistication of the most widely used technology, and depends multiplicatively on two shifters, one firm-specific (C_j) and one that is specific to the business function and the firm characteristics X ($C_{f,X}$).

The firm selects the sophistication level in each function to maximize the operating profits net of adoption costs, $\Pi_j(a_j) - \sum_{f=1}^{N_f} C_j C_{f,X} e^{s_{f,j}}$, subject to equation (6). As shown in Appendix D, the optimal sophistication levels of the most widely used technologies can be characterized as

$$s_{f,j} = \kappa_j + \kappa_f + \varepsilon_f * a_j - \sigma ln(C_{f,X}) \tag{8}$$

where κ_j and κ_f are firm and function-level fixed effects. Equation (8) shows that $s_{f,j}$ decreases with the marginal cost of sophistication and increases with the marginal benefits of sophistication. Aside from the function and firm fixed effects, the marginal costs of sophistication are represented by the non-separable term $C_{f,X}$. The marginal benefits of

[60] See Appendix D for details.

[61] γ_j in equation (7) is the product of the first two terms.

technological sophistication in a business function vary with the firm's technology index, a_j, defining a relationship that we refer to as the *Technology Curve*.

Due to the non-homothetic nature of the technology index (6), the slope of the technology curve, ε_f, differs across business functions. Functions with higher ε_f are more "technology elastic" because the marginal benefit from sophistication in the function increases more with a_j. As we show next, the technology index (a_j) and the non-separable component of the marginal cost of adoption ($C_{f,X}$), not only drive $s_{f,j}$, but also determine the within-firm variance in technology sophistication.

Within-firm variance in sophistication

Expression (8) implies that the residual in sophistication after removing firm and function effects is $u_{f,j} = \varepsilon_f * a_j - \sigma * ln(C_{f,X})$. Therefore, the within-firm variance in sophistication for firm j is equal to

$$WVar_j = a_j^2 Var(\varepsilon_f) + \sigma^2 Var(ln(C_{f,X})) - 2a_j \sigma Cov(\varepsilon_f, ln(C_{f,X})) \tag{9}$$

Suppose that ε_f and $ln(C_{f,X})$ are uncorrelated across functions so that the covariance term in equation (9) drops out. Under this simplifying assumption, there are two possible sources of variance in sophistication across the business functions of a firm. First, heterogeneity in ε_f causes the marginal benefit of sophistication to grow at different rates across functions, inducing the dispersion in sophistication across functions to increase with the technology index (a_j). This mechanism corresponds to the first term in expression (9). Second, cross-function heterogeneity in the non-separable component of the marginal cost of adoption ($C_{f,X}$) also induces firms to implement different sophistication levels across functions. This channel is captured by the second term in equation (9).

At this point, is it natural to wonder about the relative importance of marginal costs and marginal benefits of technology sophistication for within-firm variance in sophistication. The estimates from Table 6 can start to shed light on this question. Some firm characteristics have the property that their correlation with the marginal costs of adoption varies across functions. These firm characteristics induce cross-function variance in $C_{f,X}$ and in technology sophistication (see equation 9). One such characteristic is firm size. Smaller firms are more likely to suffer from limited technical capacity and access to finance. Since the technical knowledge and sunk costs required to implement more sophisticated technologies vary across business functions, small firms will have low marginal cost, $C_{f,X}$, in functions where these requirements are minimal but very high marginal costs in functions where technical knowledge and/or sunk costs of implementation are significant. As a result, the variance of $C_{f,X}$ should be diminishing in firm size. Furthermore, if heterogeneity in the marginal costs of adoption is an important driver of within-firm variance in sophistication, we should observe that within-firm variance should be decreasing in firm size. Table 6 shows, however, that the variation in technology sophistication across the functions of a firm is uncorrelated with firm size, suggesting that heterogeneity in adoption costs is not the main driver of within-firm variance in technology.

In contrast, the strong positive association between within-firm dispersion in sophistication and average sophistication of a firm is consistent with the presence of non-homotheticities in production, as illustrated by the first term of (9). This finding suggests that heterogeneity across business functions in the benefits from improving technology is a key driver of within-firm variance in technology.

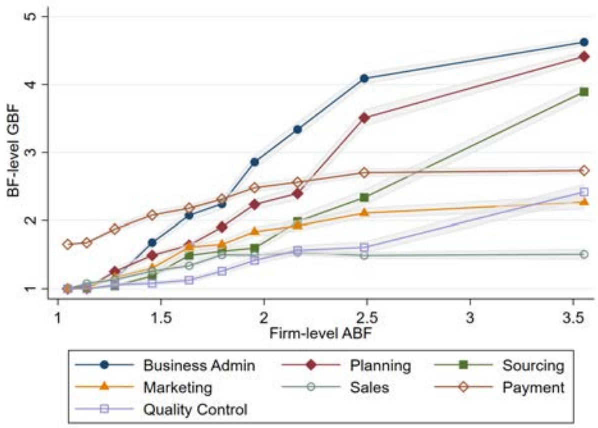
5.3 The Technology Curve

In this section, we directly investigate the presence of technology curves. We start with a graphical exploration before estimating the specification for the technology curves predicted by our model. The estimates allow us to quantify the contribution of the technology curves to the within-firm variance in technology sophistication. We conclude by demonstrating the robustness of the findings.

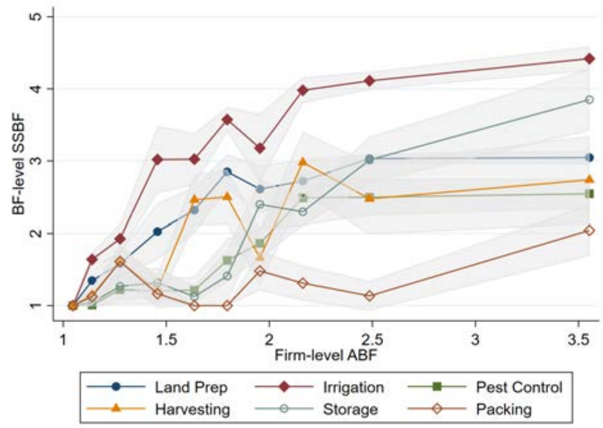
We collapse firms into deciles of the distributions of s_j and the within-firm dispersion in sophistication, respectively. Figure 8 plots, for the firms in each decile of the distribution of s_j, the average value of $s_{f,j}$ (vertical axis) against the average of s_j (horizontal axis). For example, in the top left panel of Figure 8 we observe that the average sophistication level in "payments" for firms in the bottom decile of the distribution of average sophistication is 1.7, while the average sophistication for these firms is 1.1. Figure 9 plots the equivalent relationship but now deciles are formed based on the distribution of within-firm dispersion in sophistication ($WVar_j$) which is graphed in the horizontal axis. The top panel plots the technology curves for the seven GBFs, while the other four panels plot the technology curves for the SSBFs in the four sectors with most firms in sample (crops-agriculture, food processing, apparel, and retail and wholesale).[62]

Figures 8 and 9 reveal interesting patterns. Not surprisingly, technology curves are upward sloping. That is, as we move to higher deciles in the distribution of average firm sophistication and within-firm dispersion, the sophistication in any given business function tends to increase. However, the slope of the technology curves varies significantly across business functions. For example, among the GBFs, the most technology-elastic (i.e., largest

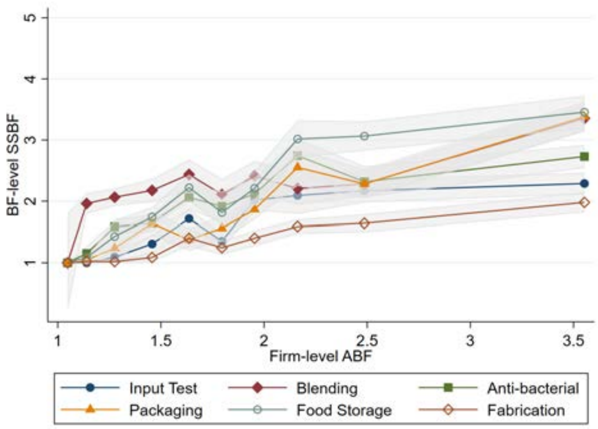
[62] These are sectors for which the survey was stratified in all countries. Additionally, we plot 95% confidence bands in the technology curves.



(a)



(b)



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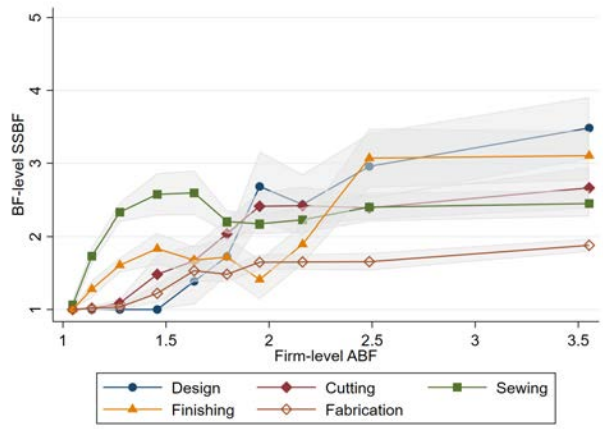

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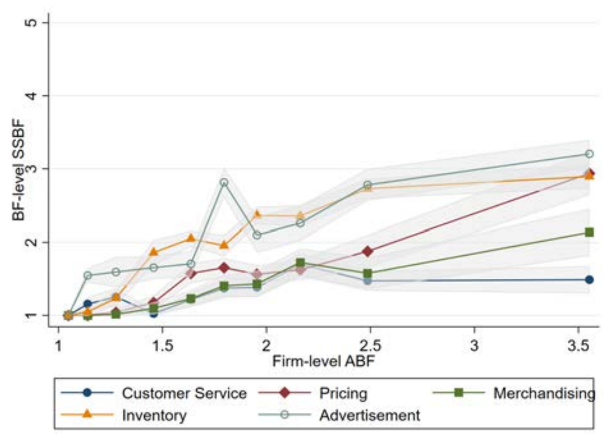


(e)

Figure 8: The Technology Curve, $s_{f,j}$ vs. s_j by Deciles

slope) functions are business administration and planning, while the least technology-elastic is sales. SSBFs also display heterogeneity in the slope of technology curves. The most technology-elastic functions in each sector are irrigation in agriculture, design and finishing in apparel, packaging in food processing, and advertising and inventory in retail and wholesale. Finally, these patterns are quite similar in technology curves based on s_j and based on within-firm dispersion. As we shall see next, this is a prediction of the model developed in the previous subsection.

To explore more formally the technology curves, we use the model to derive a reduced-form specification. Substituting the first order approximation of a_j from equation (7) into (8), imposing that $\gamma_j = \gamma\ \forall j$, and assuming that $ln(C_{f,X})$ is additively separable into a function and a firm effect,[63] we obtain the following specification for the Technology Curve:

$$s_{f,j} = \alpha_j + \alpha_f + \varepsilon_f^{\beta}\left(s_j + \varrho * \sqrt{WVar_j}\right) + v_{f,j} \tag{10}$$

where $s_{f,j}$ is the technology sophistication of firm j in function f, s_j is the average technology sophistication in firm j, α_f and α_j are function and firm fixed effects, ϵ_f^{β} is the technology-elasticity of business function f, and $v_{f,j}$ is an error term.[64]

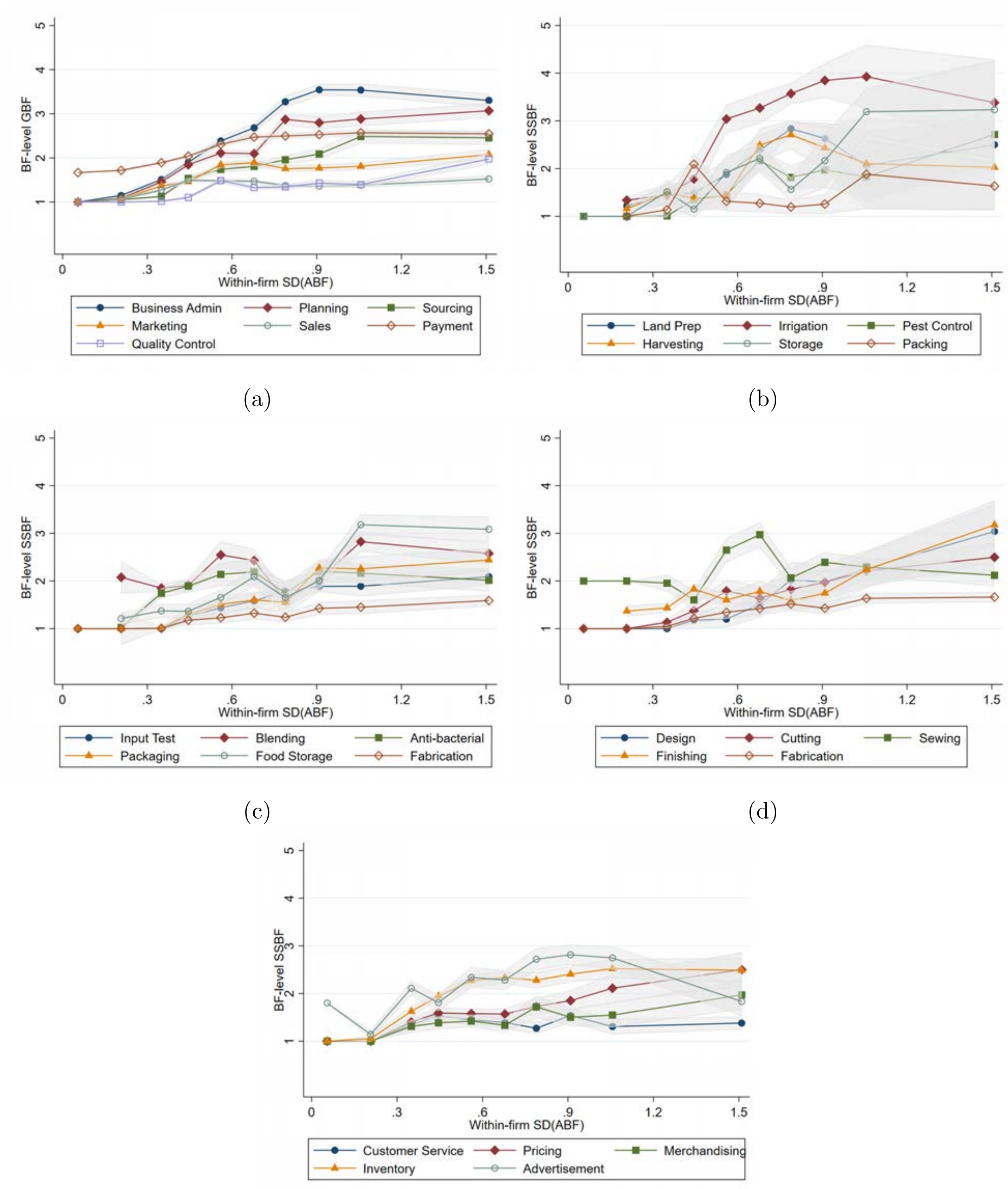
We estimate specification (10) using non-linear least squares imposing the constraint that ϱ is constant across business functions.[65] Table 7 reports the point estimates and their standard errors for each general business functions and the sector-specific business functions in the four largest sectors. We also report the fraction of the within-firm variance in $s_{f,j}$ explained by the technology curve in each broad group of business functions. Our estimates reveal three key findings. First, there are large, statistically-significant differences in the point estimates of the slopes of technology curves across business functions. For GBFs, these vary from 1.81 in business administration to 0.25 in sales. For the SSBFs, the range is comparably wide though it varies across sectors.[66] Second, we estimate a positive and significant value for ϱ that suggests the relevance of both average sophistication and within-firm variance for the construction of the firm technology index a_j. Third, the within-firm

[63] Alternatively, our estimates are unbiased if $ln(C_{f,X})$ is uncorrelated to s_j and $\sqrt{WVar_j}$. The latter requirement is supported by Table 6. We have further estimated a version of the technology curve where we proxy $ln(C_{f,X})$ by a function-level fixed effect interacted with log firm employment. This formulation captures the possibility that firm size affects the marginal cost of increasing technology sophistication differently across business functions. Table E.7 in the Appendix reports the estimates of the slope of the technology curve for the GBFs and the four main SSBFs. We find that the point estimates are very close to the baseline in Table 7.

[64] $\varepsilon_j^{\beta} = \frac{(1-\sigma)\varepsilon_f}{\overline{\varepsilon}}$, where $\overline{\varepsilon} = \sum_f \omega_f \varepsilon_f$ is the weighted average of ε_f. Importantly, since the weights ω_f come from the first order approximation of a_j around the average firm in (7), they are the same across firms. See Appendix D for details.

[65] See Appendix D for details about the estimation and the point estimates for all business functions.

[66] In crop agriculture, the estimates of the technology-elasticity vary from 2.01 for irrigation to 0.30 for packaging. The range is smallest in wholesale and retail where the most technology elastic function is inventory (0.72) and the least customer service (0.05).



(e)

Figure 9: The Technology Curve, $s_{f,j}$ vs. Within-firm Dispersion in Sophistication by Deciles

R^2 is 0.32,[67] implying that, despite its simplicity, the technology curve accounts for a very significant share of the large variance observed within firms in technology sophistication.

Table 7: Technology Curve

General Business		Agriculture - Crops		Food Processing		Wearing Apparel		Wholesale & Retail	
ϵ^{β}_{Admin}	1.81*** (0.01)	$\epsilon^{\beta}_{Irrigation}$	2.01*** (0.24)	$\epsilon^{\beta}_{FoodStorage}$	1.04*** (0.20)	$\epsilon^{\beta}_{Design}$	1.01*** (0.15)	$\epsilon^{\beta}_{Inventory}$	0.72*** (0.05)
$\epsilon^{\beta}_{Planning}$	1.59*** (0.03)	$\epsilon^{\beta}_{Storage}$	1.53*** (0.24)	$\epsilon^{\beta}_{Packaging}$	0.84*** (0.19)	$\epsilon^{\beta}_{Cutting}$	0.77*** (0.14)	$\epsilon^{\beta}_{Advert}$	0.72*** (0.08)
$\epsilon^{\beta}_{Sourcing}$	1.25*** (0.03)	$\epsilon^{\beta}_{LandPrep}$	1.50*** (0.22)	$\epsilon^{\beta}_{InputTest}$	0.63*** (0.22)	$\epsilon^{\beta}_{Finishing}$	0.56*** (0.15)	$\epsilon^{\beta}_{Pricing}$	0.62*** (0.06)
$\epsilon^{\beta}_{Marketing}$	0.66*** (0.03)	$\epsilon^{\beta}_{Harvest}$	1.21*** (0.24)	$\epsilon^{\beta}_{AntiBact}$	0.61*** (0.21)	$\epsilon^{\beta}_{Fabrication}$	0.20 (0.14)	$\epsilon^{\beta}_{Merchand}$	0.34*** (0.06)
$\epsilon^{\beta}_{Quality}$	0.62*** (0.04)	$\epsilon^{\beta}_{PestControl}$	1.08*** (0.25)	$\epsilon^{\beta}_{Blending}$	0.34* (0.19)	$\epsilon^{\beta}_{Sewing}$	0.19 (0.15)	$\epsilon^{\beta}_{CustomServ}$	0.05 (0.06)
$\epsilon^{\beta}_{Payment}$	0.56*** (0.03)	$\epsilon^{\beta}_{Packaging}$	0.30 (0.27)	$\epsilon^{\beta}_{Fabrication}$	0.30* (0.18)				
ϵ^{β}_{Sale}	0.25*** (0.03)								
ϱ	0.17*** (0.02)								
Within-firm R^2	0.32								

Note: *** p<0.01, ** p<0.05, * p<0.1. Business function-level technology sophistication is regressed on firm-level technology sophistication using nonlinear least-squares estimation. The parameter ϵ^{β}_{f} for general business functions and ϱ are reported in this table. Estimates are weighted by the sampling weights. Standard errors in parentheses.

Robustness

We study the robustness of the estimated technology curves to variations in the procedure used to construct the business function-level technology sophistication measures. Specifically, we consider alternative cardinalizations of technology rankings, and alternative approaches to determine the most sophisticated technology in the technology grid for each business function.

Alternative cardinalization of sophistication index First, we explore the robustness of the technology curve to using alternative values of ϕ to construct the sophistication measures, $s^{\phi}_{f,j}$.[68] Columns 2 and 3 of Table 8 report the slopes and fit of the technology curves in GBFs estimated using sophistication measures computed with $\phi = 1/3$ and 3, respectively. Comparing the estimates with our baseline (column 1), we observe that, although

[67] See Tables 7, E.5, and E.6. For the broad classes of business functions reported in Table 7, the within-firm R^2 ranges from 25% to 37%

[68] Naturally, the average firm sophistication and the within-firm dispersion measures are recomputed with the relevant $s^{\phi}_{f,j}$.

Table 8: Technology Curve, Robustness

Parameters	(1) Baseline	(2) $\phi = 1/3$	(3) $\phi = 3$	(4) Max-1	(5) Observed Max
ϵ^{β}_{Admin}	1.81***	1.30***	2.72***	1.83***	1.85***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
$\epsilon^{\beta}_{Planning}$	1.59***	1.19***	2.51***	1.61***	1.62***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
$\epsilon^{\beta}_{Sourcing}$	1.25***	1.01***	1.66***	1.26***	1.27***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
$\epsilon^{\beta}_{Marketing}$	0.66***	0.84***	0.41***	0.68***	0.68***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)
$\epsilon^{\beta}_{Quality}$	0.62***	0.63***	0.36***	0.74***	0.61***
	(0.04)	(0.03)	(0.07)	(0.04)	(0.04)
$\epsilon^{\beta}_{Payment}$	0.56***	0.25***	0.35***	0.52***	0.70***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
ϵ^{β}_{Sale}	0.25***	0.58***	0.17***	0.24***	0.27***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
ϱ	0.17***	0.56***	-0.06***	0.16***	0.06***
	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)
Within-firm R^2	0.35	0.30	0.47	0.35	0.35

Note: *** p<0.01, ** p<0.05, * p<0.1. In the first specification, business function-level technology sophistication is regressed on firm-level technology sophistication using nonlinear least-squares estimation. In the second and third specifications, we use $\phi = 1/3$ and $\phi = 3$, respectively. In the fourth specification, we compute ABF by changing denominator from max to max-1. In the fifth specification, we compute ABF by using observed max of technology as a denominator. Each business function is estimated relative to the base business function (business administration). The parameter ϵ^{β}_{f} for general business functions and ϱ are reported in this table. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

the estimates of the slopes of the technology curve vary with ϕ, (i) in all cases there is large heterogeneity across business functions in the estimated slopes, (ii) that the differences in slopes across functions are always statistically significant, (iii) that the ranking of business functions according to the estimated slopes are almost identical for all three cardinalizations, and (iv) that the technology curves account for a large share of the variation in technology sophistication within firms. The only parameter estimate that is sensitive to the parameterization of ϕ is ϱ which becomes negative when $\phi = 3$. Despite that, we can conclude that the key findings from our exploration of technology curves are robust to alternative (plausible) cardinalizations of technology rankings.[69]

[69] Figures G.1 to G.5 plot for each GBF and SSBF in the largest four sectors, the technology curves for $\phi = 1/3, 1, 3$. The Figures show the robustness of the key findings to alternative cardinalizations of the technology sophistication rankings.

Most sophisticated technology in the business function A second potential concern about the technology curves may originate from the presence of measurement error in the definition of the maximum possible sophistication across business functions. Measurement error could arise if experts used different criteria to determine the most sophisticated technologies across business functions. For example, in some business functions, the experts may include among the possible technologies some that are more experimental.[70] We explore the relevance of measurement error in the best possible technologies conducting two exercises. The first consists in scaling the sophistication ranking of the most widely used technology by the maximum sophistication ranking minus one (instead of by the maximum sophistication ranking as we do in the baseline). In this way, we reduce the concern that in some functions the best possible technology is still too experimental and not fully developed while in others it is not. The second exercise consists in scaling the sophistication ranking of a technology by the highest sophistication observed in the sample. In this way, we eliminate from the list of possible technologies those that maybe out of reach for all the firms in our sample.

Columns 4 and 5 of Table 8 report the estimates of the technology curves in these two exercises. Again, both the goodness of fit and the point estimates of the slopes of the technology curves are very robust to these alternative calculations. Heterogeneity in the technology curves across BFs is robust to potential errors in the identification of the most sophisticated technologies.

Summing up, we have demonstrated the existence of a technology curve that defines the cross-firm relationship between sophistication in a business function and the firm-level technology index. There is great heterogeneity across business functions in the slope of technology curves. Furthermore, the technology curve captures much of the cross-firm business function-level variation in sophistication and that. These findings are important as they demonstrate the presence of non-homotheticicities in the firm-level technology index.

6 Technology sophistication and firm productivity

After characterizing technology sophistication across and within firms, we explore the relationship between technology sophistication and firm-level productivity. First, we discuss the channels by which technology sophistication may impact productivity. We conclude the section with a development accounting exercise that computes the variation in cross-firm

[70] Note however, that the same experts define the range of possible technologies of all the business functions in a sector (or of the GBFs). Thus, for this to be a relevant concern the same experts should be inconsistent in their criteria to determine the best possible technologies across the business functions of the sector they focus on. Furthermore, we explicitly instructed consultants and technology experts against the inclusion of experimental technologies in the grid.

productivity accounted for by differences in the distribution of technology sophistication across firms.

6.1 Theoretical considerations

To explore the relationship between labor productivity and the technology index (a_j), consider a firm with technology index a_j that has access to the (value added) production function $F_j(a_j, L_j, K_j)$ where L_j is the number of workers, and K_j the capital stock. Cost minimization yields the following expression for the level of nominal value added per worker:

$$\frac{P_j F_j}{L_j} = \frac{P_j}{\lambda_j} \frac{W}{\epsilon_{F,L}} \tag{11}$$

where W is the (exogenous) wage rate, P_j is the price of the output produced by firm j, λ_j its marginal cost of production, and $\epsilon_{F,L} = \frac{\frac{\partial F_j(a_j, L_j, K_j)}{\partial L_j} L_j}{F_j}$ is the elasticity of output with respect to labor in firm j. Taking logs and differentiating with respect to a_j, the effect of the technology index on firm-level productivity is

$$\frac{\partial ln(\frac{P_j F_j}{L_j})}{\partial a_j} = \frac{\partial ln(\frac{P_j}{\lambda_j})}{\partial a_j} - \frac{\partial \epsilon_{F,L}}{\partial a_j} \tag{12}$$

Expression (12) illustrates two possible channels by which a_j may affect value added per worker. The first is through the markup ($\frac{P_j}{\lambda_j}$). Under imperfect passthrough, changes in the technology index affect the marginal cost of production more than the price, and hence the markup. As a result, increases in the sophistication of the technology have a positive effect on firm productivity.[71]

The second term in equation (12) represents the effect of the technology index on the elasticity of output with respect to labor. If the elasticity declines with a_j, for example, because the production process becomes more capital intensive when a_j increases, or because the overhead costs per unit of output decline with a_j, increases in technology lead to higher labor productivity.[72]

[71] Suppose that $P_j = \phi \lambda_j^{\gamma_j}$, where $\gamma_j \in (0, 1)$ is firm's j passthrough. Then, the first term in (12) is $\frac{\partial ln(\frac{P_j}{\lambda_j})}{\partial a_j} = -(1 - \gamma_j) * \frac{\partial ln(\lambda_j)}{\partial a_j} > 0$.

[72] See Appendix D for specific examples of these production functions.

6.2 Empirics

Baseline specification

Combining equations (12) and (7), we can specify the following reduced-form relation between the log of nominal value added per worker ($ln(VAPW)$) and the technology sophistication measures:

$$ln(VAPW)_{j,c} = \alpha_c + \beta_s + \zeta * s_j + \gamma * \sqrt{WVar_j} + \rho * X_{j,c} + v_{j,c} \tag{13}$$

where α_c and β_s are country and sector fixed effects,[73] X_j is a vector of controls that includes the observables introduced in section 4.4, and the dependence of productivity on both average firm-level sophistication (s_j) and within-firm variance in sophistication ($WVar_j$) arises from the first order relationship between the firm-level technology index (a_j) and the sophistication measures in (7).

The estimates of (13) are reported in Table 9. Column 1 shows that there is a positive association between firm-level productivity and average technology sophistication (s_j). Column 2 introduces a quadratic in s_j and finds that the relationship between productivity and average sophistication is concave. This observation is consistent, although independent, from the finding in Table 1 that a slightly concave cardinalization of the sophistication rankings can match the skewness of the distribution of firm-level productivity levels. Comparing the R^2 in the first two columns of Table 9 we observe that the quadratic term, though statistically significant, does not increase much the power of the model to explain cross-firm variance in labor productivity.[74]

Next, we turn our attention to the relationship between productivity and within-firm dispersion of sophistication across business functions. Equations (12) and (7) imply that firm productivity should be positively associated with within-firm dispersion in sophistication after controlling for s_j. Intuitively, for a given average sophistication, productivity is greater if the firm can allocate more sophisticated technologies to functions that have a greater weight in the technology index. Mathematically, this translates into a positive productivity effect of the covariance between technology sophistication and function weights. For a given (positive) correlation between these two variables, the covariance is increasing in the within dispersionn technology. Hence, the presence of $\sqrt{WVar_j}$ in (13).

[73] These include twelve dummies for the sectors for which we have sector-specific technologies plus other services. The left-out sector is crop agriculture.

[74] We provide additional robustness checks on the relationship between productivity and technology sophistication in Appendix G. We show that our results are robust if we control for capital per worker and labor cost per worker, if we use alternative cardinalization parameters of technology sophistication, and if we control for 4-digit sector disaggregation.

Table 9: Productivity and Technology Sophistication

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.73***	2.80***	0.58***		2.18***	2.01***
	(0.10)	(0.49)	(0.11)		(0.58)	(0.62)
s_j^2		-0.47***			-0.36***	-0.18
		(0.10)			(0.12)	(0.15)
SD_j			0.71***		0.55***	1.95***
			(0.15)		(0.17)	(0.51)
a_j				0.74***		
				(0.10)		
$s_j \times SD_j$						-0.71***
						(0.22)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.48	0.49	0.49	0.48	0.49	0.50

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

Column 3 of Table 9 shows that, conditional on s_j there is a positive association between firm productivity and the dispersion in sophistication across the business functions of a firm.[75] The coefficient is not just statistically but also quantitatively significant in terms of its contribution to the variation in firm productivity that sophistication measures account for. Average firm sophistication accounts for 57% of the variation in firm-productivity explained by firm-sophistication, while the within-firm dispersion accounts for 43%. Column 6 explores whether the relationship between productivity and within-firm dispersion in sophistication varies with average firm sophistication (s_j). We find that the relationship is stronger for firms with lower average sophistication. From equation (7) this finding suggests a higher correlation between technology sophistication and function weights in firms with lower average sophistication.

For robustness, we restrict the specification in (13) by using the estimates of ϱ in Table 7 to replace s_j and the within-firm dispersion by the first order approximation of the technology index a_j, constructed as the linear combination of s_j and the within-firm dispersion in sophistication.[76] Column 4 of Table 9 shows that there is a strong association between our

[75]For brevity, the within-firm dispersion in sophistication is denoted by SD_j in the tables.

[76]Recall that this proxy results from a first-order approximation of the technology index a_j under the additional restriction that the correlation across functions between weights and sophistication levels is constant across firms. This restriction seems to be rejected by the estimate of the interaction between SD_j and s_j in column 6 of Table 9. Despite this finding, it is interesting to study the association between the proxy

approximation of the technology index and firm productivity, and that the point estimates and fit are very similar to those in the first three columns of Table 9.

We further explore the relationship between firm-technology measures and productivity by investigating whether this relationship operates through TFPR.[77] To this end, we include as controls in regression (13) the book value of capital per employee in the firm and the cost of labor per worker as a proxy for the average human capital per worker. The results from this exercise are reported in Appendix Tables F.8 (which controls for capital per worker) and F.10 (which includes the controls for both capital and human capital per worker). The key take away is that the estimates in Table 9 are robust to controlling for firm-level capital per worker and average human capital. Hence, we conclude that the strong relationship between firm productivity and sophistication measures largely reflects the relationship between sophistication and firm TFP.

Heterogeneity in the relationship between sophistication and productivity

To better understand the relationship between technology sophistication and firm productivity, we explore the presence of two forms of heterogeneity. First, we study whether the association between technology sophistication and productivity differs between GBFs and SSBFs. Second, we study whether the association between the sophistication measures and firm productivity varies across sectors.

To explore these questions, we modify the specification in (13) and separate s_j into the average sophistication of a firm's GBFs and SSBFs. Because the functions included in SSBFs vary across sectors, we allow their coefficient to differ across sectors. In column 1, we consider the three traditional sectoral divisions of the economy (i.e., agriculture, manufacturing and services). In columns 2 and 3, we use an alternative sectoral grouping which splits manufacturing between apparel, food processing and other manufacturing and services between retail and wholesale and other services (the left-out group). In addition to the potentially heterogenous effects of average firm sophistication, the specifications include as control within-firm dispersion in sophistication (imposing a common coefficient across sectors).

Column 1 of Table 10 shows that firm productivity is positively related to the average sophistication in both GBFs and SSBFs. The coefficient on the average sophistication in SSBFs differs significantly across sectors. It is greatest in agriculture, then manufacturing, and insignificant in services. Looking inside manufacturing, we find that the coefficients of average sophistication in SSBFs for food processing and especially apparel are comparable

for a_j and firm-level productivity.

[77] See Hsieh and Klenow (2009).

Table 10: Productivity and Technology Sophistication, Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.53***	0.55***	
	(0.10)	(0.10)	
s_j^{GBF}*Agriculture			0.46
			(0.29)
s_j^{GBF}*Manufacturing			0.67***
			(0.11)
s_j^{GBF}*Services			0.52***
			(0.11)
s_j^{SSBF}*Agriculture	0.61***		
	(0.21)		
s_j^{SSBF}*Manufacturing	0.29***		
	(0.09)		
s_j^{SSBF}*Services	-0.07		
	(0.15)		
s_j^{SSBF}*Agriculture		0.61***	0.66***
		(0.21)	(0.21)
s_j^{SSBF}*Food Processing		0.42**	0.37*
		(0.19)	(0.19)
s_j^{SSBF}*Apparel		0.65***	0.59***
		(0.15)	(0.16)
s_j^{SSBF}*Retail and Wholesale		-0.12	-0.09
		(0.16)	(0.17)
s_j^{SSBF}*Other Manufacturing		0.14	0.10
		(0.09)	(0.09)
SD_j	0.69***	0.69***	0.67***
	(0.16)	(0.16)	(0.16)
Firm Characteristics	$\surd$	$\surd$	$\surd$
Observations	2,746	2,746	2,746
R-squared	0.49	0.49	0.49

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

in magnitude to the coefficient for agriculture, but the sophistication in the SSBFs of the remaining manufacturing sectors are insignificantly associated with firm productivity. In column 3 we explore whether the association between the average sophistication of GBFs and firm productivity differs across sectors. We find similar point estimates across the three sectors, though the coefficient for agriculture is not statistically significant.[78]

[78]Note further that the point estimates of the coefficient of within-firm dispersion in sophistication across business functions are not affected by allowing for sectoral and business function heterogeneity in the coefficients.

6.3 A Development Accounting Exercise

We conclude our analysis by conducting a development accounting exercise. There is a long tradition in macroeconomics, that goes back at least to Mankiw, Romer and Weil (1992), studying how different factors account for cross-country differences in productivity. This methodology has been recently extended to explore cross-firm differences in productivity. For example, Bloom and Van Reenen (2007) explore the contribution of management practices to variation in firm productivity. We use the estimates of the productivity regressions from Tables 9 and 10 to explore how much of the cross-firm dispersion in productivity firms can be accounted for by the observed cross-firm variation in technological sophistication.

To answer this question, we first compute the residual productivity for all firms by regressing productivity on the variables in (13) other than the sophistication measures, and then computing the residual. Then we calculate the gap between the 10^{th} and 90^{th} percentiles of this residual, and define this as the productivity gap. We then regress each of the sophistication measures in (13) on the observable characteristics, compute the residual and define the gap between the 10^{th} and 90^{th} percentiles of this residual as the sophistication gap. Finally we calculate the product of sophistication gap and the estimates in Tables 9 and 10, and divide by the productivity gap. This ratio is the fraction of the dispersion in firm productivity accounted for by the dispersion in technology sophistication across firms.

Table 11 reports the result from this calculation for each of the specifications. We find that cross-firm differences in technology sophistication measures account for between 24% and 31% of the differences in productivity.

Table 11: Development Accounting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
P10	-0.36	-0.42	-0.38	-0.38	-0.43	-0.50	-0.39	-0.40	-0.40
P90	0.38	0.40	0.46	0.40	0.44	0.44	0.47	0.48	0.48
% Productivity Dispersion Accounted by Technology	24%	26%	27%	25%	28%	30%	28%	28%	28%

Note: Each row presents development accounting associated with each specification used in Table 9 columns (1)-(6) and Table 10 columns (1)-(3) in order. For each specification, we run regress ln(vapw) and technology measures on firm characteristics to estimate residuals. Then, we run regress the residual of ln(vapw) on the residuals of technology measures and compute P10 and P90 of the predicted outcomes. First and second rows provide the P10 and P90 of the predicted residuals of ln(vapw), respectively. Third row reports as percentages the difference between p90 and p10 of predicted residuals of ln(vapw) divided by the overall difference between between p90 and p10 of the residuals of ln(vapw).

7 Conclusions

We have introduced the FAT survey and have administered it to a representative sample of firms in Senegal, Vietnam and the Brazilian state of Ceará. The resulting dataset contains comprehensive information about the technologies used in each of the key business functions of the companies surveyed. We have used this information to construct measures that provide a detailed characterization of the sophistication of the technologies that firms use in each of the key general and sector-specific business functions involved in their operations.

Our analysis has documented (i) large cross-country and cross-firm differences in the sophistication of technologies used in production, (ii) that the variance in technology sophistication within firms is 2.8 times larger than the variance in technology sophistication across firms, and (iii) that firms with greater average sophistication of technology also have greater variance in sophistication across their business functions.

To study the drivers of the technology sophistication across the business functions of a firm, we have developed a model of technology adoption where the marginal costs of implementing more sophisticated technologies may vary by function and firm, and where the marginal benefit of more sophisticated technologies may vary non-homothetically with the firm-level technology. The model predicts a stable linear relationship (that we have named "the Technology Curve") between the sophistication of technology in a business function and the technology index of a firm. Using our FAT data, we have documented the existence of technology curves. Our estimates demonstrate that there is large variation in the slopes of technology curves across business functions and that, despite their simplicity, technology curves explain a large fraction of the within-firm variance in technology sophistication. We have concluded our analysis by linking sophistication measures to firm-level productivity. A development accounting exercise has revealed that cross-firm differences in technology sophistication measures account for around 30% of the gap we observe between firms at the top and bottom 10% of the productivity distribution.

The dataset we have assembled and the analysis we have conducted suggest a number of directions for future research. One important goal is the construction of direct measures of firm-level productivity that reflect the "technological landscape" of the company. Our approach to measuring technology is conceptually much cleaner than the common practice of computing the Solow residual and then removing cyclical variation in factor utilization and demand-side factors that affect the residual.[79] In this paper, we have computed a first order approximation to the technology index and have studied its relationship to firm productivity. In future work we intend to identify all the parameters that define the technology index, not

[79] See for example, Basu, Fernald and Kimball (2006) and Comin et al. (2020).

just the slopes of technology curves, and to compute exact measures of the technology index that may reveal greater cross-firm variation in the technology indices than the first order approximations considered here. To estimate all the parameters in the technology aggregator while allowing for sectoral heterogeneity, it may be necessary to increase the sample size of FAT and, to this end, we are planning to administer the survey in more countries.

An important question that has attracted much attention is why the cross-country productivity gap is much larger in agriculture than in the non-agricultural sectors (Caselli, 2005). Our analysis of FAT has uncovered a potential avenue to account for part of the agricultural productivity gap. Specifically, cross-country variation in technology sophistication (especially in SSBFs) is larger in agriculture than in other sectors, and more sophisticated technologies are particularly important for agricultural productivity. Further exploration of this evidence seems worthwhile. In particular, we intend to revisit this question once we estimate exact firm-level technology indices that help us account for sectoral variation in the importance of technology sophistication across business functions.

Finally, we plan to explore how the approach set out in this paper can be used to design more effective technology adoption policies. In particular we intend to study whether policy interventions aimed at reducing the costs of adopting more sophisticated technologies should consider in their design the non-homotheticities that we observe in FAT.

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Contents (Appendix)

A The FAT survey and results referred to in Section 2

This section provides more details on the FAT survey and its implementation in support to section 2 of the main text. Its subsections include a description of all grid of technologies in FAT, the sampling framework, the construction of sampling weights, descriptive statistics, and the tests we conducted to investigate potential biases, including validation exercises with with external data sources.

The Firm-level Adoption of Technologies (FAT) dataset is based on multi-country, multi-sector, representative firm-level surveys. The FAT dataset provides information on the technologies used by firms in specific business functions that encompass the key activities that each firm conducts. Compared to existing firm-level surveys, the FAT survey covers a significantly larger number of technologies and business functions (Table A.1), and a wider range of sectors – for example, it covers agriculture distinguishing between crops and livestock. In addition to the information on the technologies used by firms, the survey also collects balance sheet information, information on the business owners, employees, and on potential drivers of and barriers to technology adoption.

The data used in this paper corresponds to the first phase of the survey implementation. The survey was administered between June 2019 and March 2020 (i.e., pre-COVID-19 pandemic), by the World Bank in partnership with public or private local agencies across three countries: Brazil (the state of Ceará), Senegal, and Vietnam.[80]

Table A.1: Coverage of Firm-Level Technology Surveys

Surveys	# of Technologies	# of Business Functions	Includes Firms in Agriculture
Firm-level Adoption of Technology Survey	287	59	Yes
Survey of Advanced Technology (SAT)	57	3	No
Community Survey on ICT Usage and E-Commerce in Enterprises	9	0	No
Information & Communication Technology Survey (ICTS)	4	0	No
Annual Business Survey (ABS) 2019	5	0	No

Note: The Number of technologies and business functions are computed by authors.

A.1 Business functions and relevant technologies

We construct a technology grid that identifies the main business functions and the key technologies used to carry out the tasks of each business function. Modules B and C of the FAT survey collect information on these technologies. To identify business functions and technologies, we applied the procedures described in section 2. We began reviewing journal

[80]The survey second phase, conducted post COVID-19, will include other countries: Bangladesh, India (the states of Tamil Nadu and Uttar Pradesh), Ghana, Malawi, Kenya, Poland, and the Republic of Korea.

articles and technical reports to map the different business functions and specific technologies. Based on this initial research, we implemented several internal review processes with sector specialists at the World Bank Group to confirm these business functions and technologies for each sector. Then, we implemented a thorough external review process with senior private sector technology experts outside of the World Bank. These experts had experience in production processes in each specific sector of both advanced and developing countries, so they could easily map the variety, scope and complexity of different technologies.

Here, we present all sector specific business functions and associated technologies covered by the FAT survey. These figures complement the information provided in section 2, particularly Figures 1 and 2, which describe the functions and associated technologies for GBFs and food processing, among SSBFs. The complementary information is provided for all GBFs (Figure A.1) and SSBFs (Agriculture - Crops (Figure A.2), Livestock (Figure A.3), Food Processing (Figure A.4), Wearing Apparel (Figure A.5), Leather and Footwear (Figure A.6), Automotive (Figure A.7), Pharmaceutical (Figure A.8), Wholesale and Retail (Figure A.9), Transportation (Figure A.10), Financial Services (Figure A.11), Health Services (Figure A.12), and Other Manufacturing (Figure A.13)).

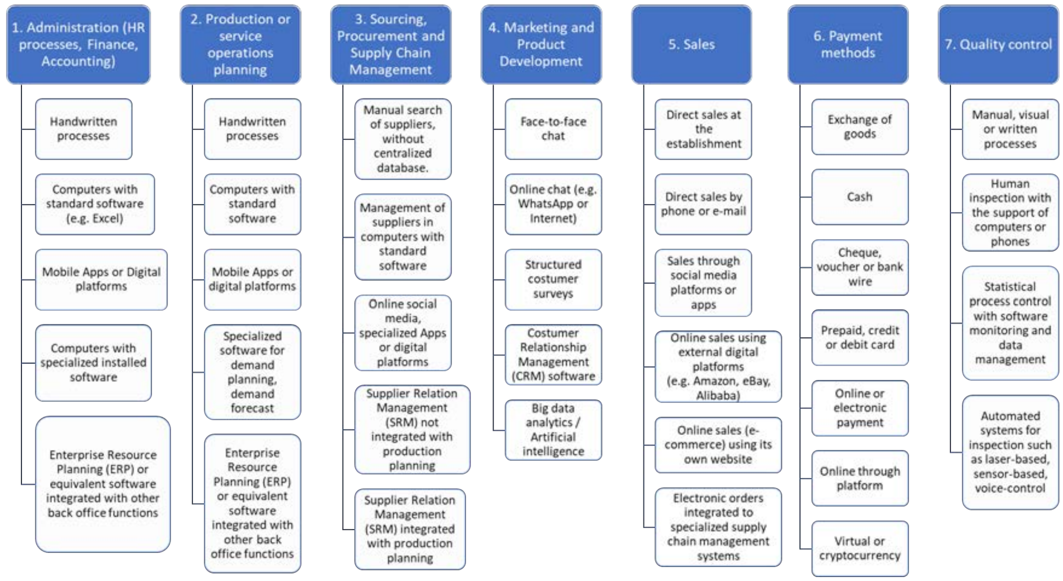


Figure A.1: General Business Functions and Their Technologies

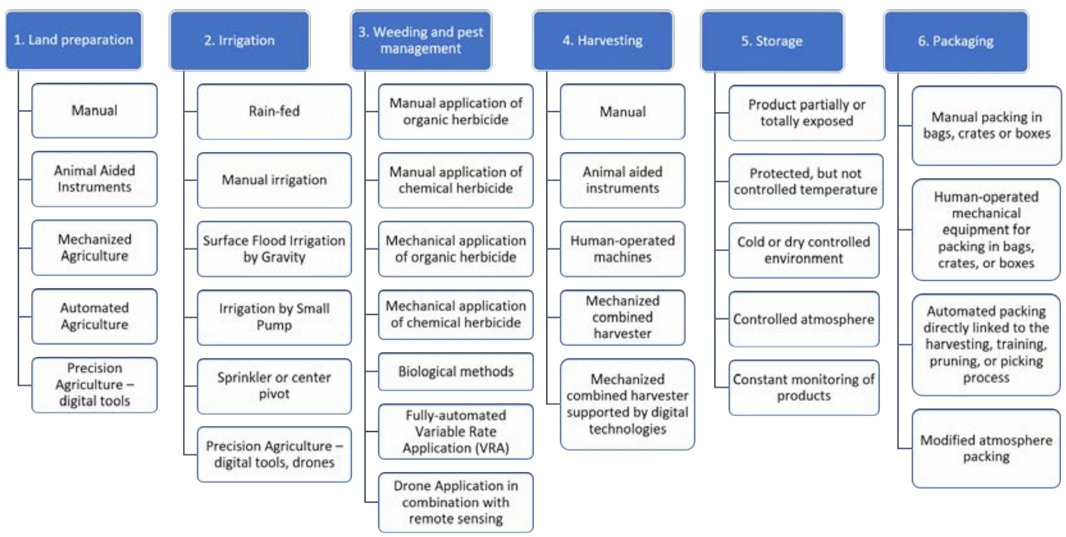


Figure A.2: Agriculture - Crops: Business Functions and Technologies

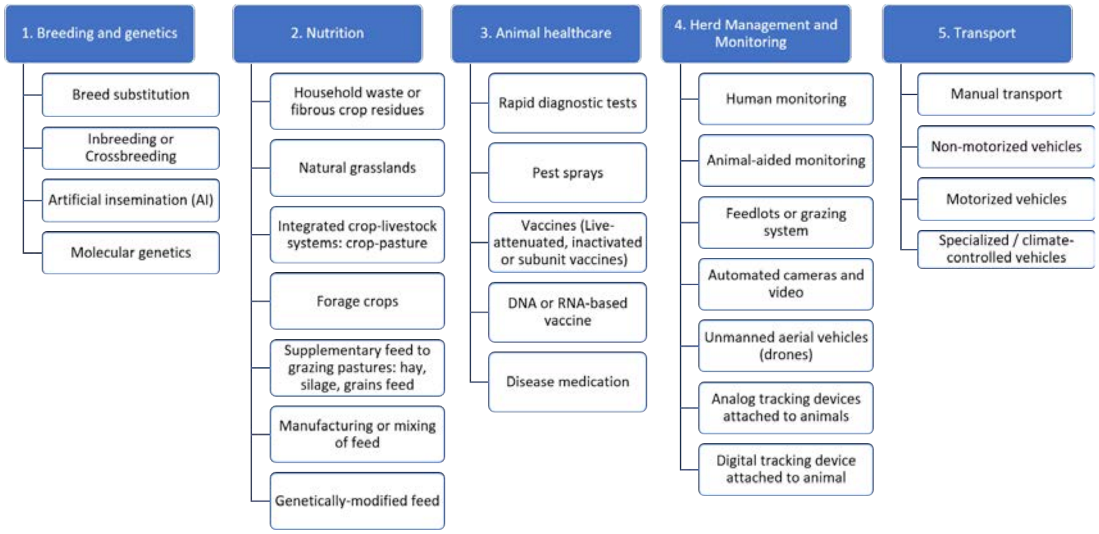


Figure A.3: Agriculture - Livestock: Business Functions and Technologies

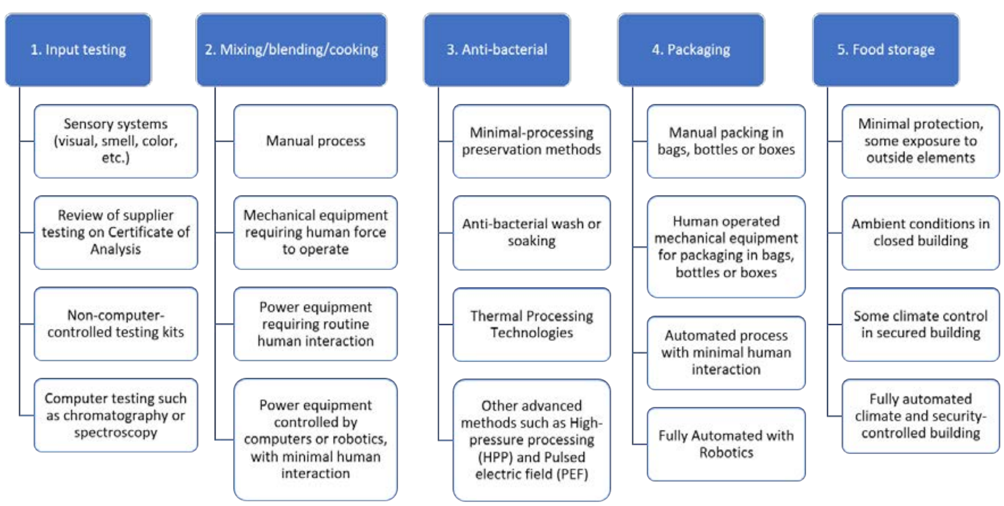


Figure A.4: Food Processing: Business Functions and Technologies

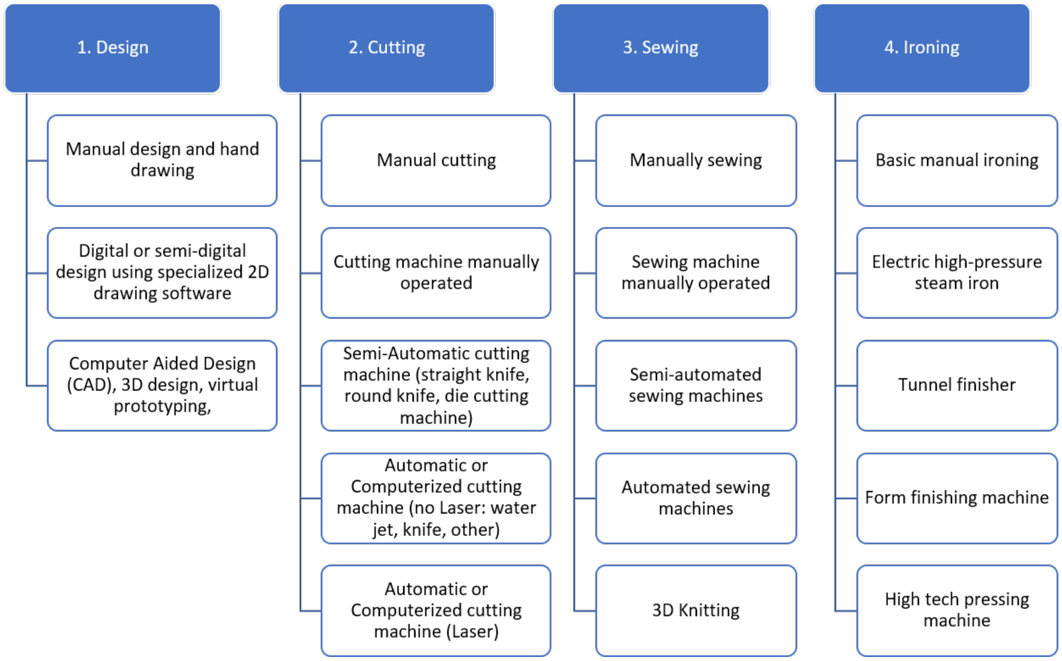


Figure A.5: Wearing Apparel: Business Functions and Technologies

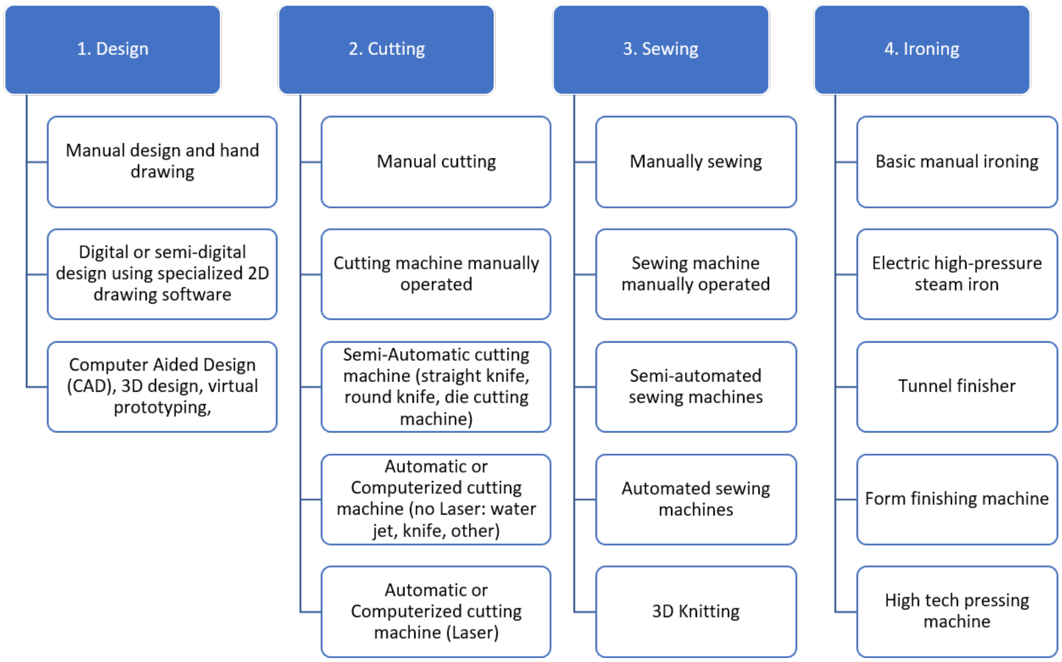


Figure A.6: Leather and Footwear: Business Functions and Technologies

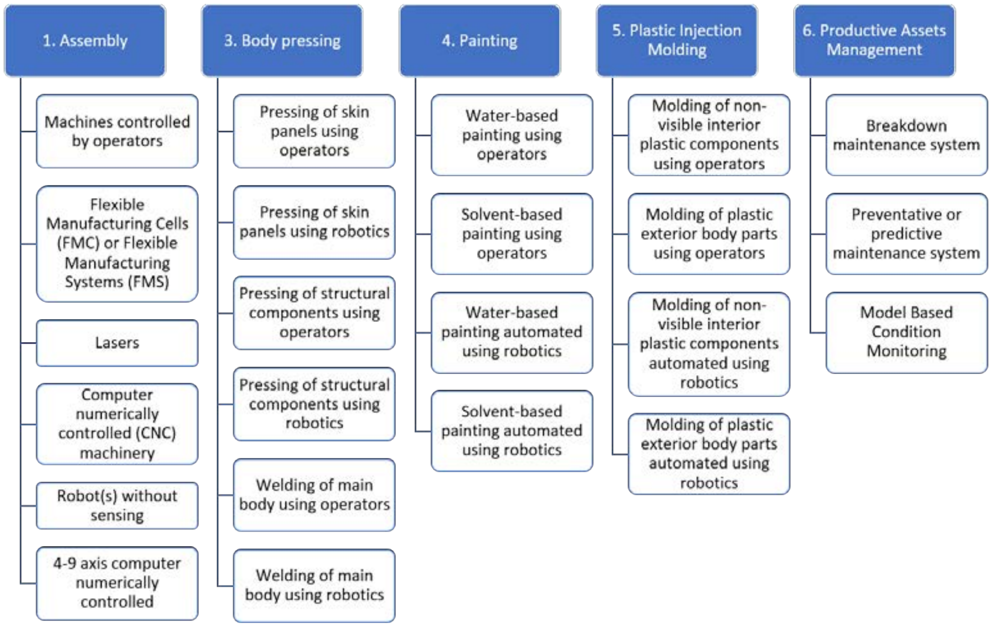


Figure A.7: Automotive: Business Functions and Technologies

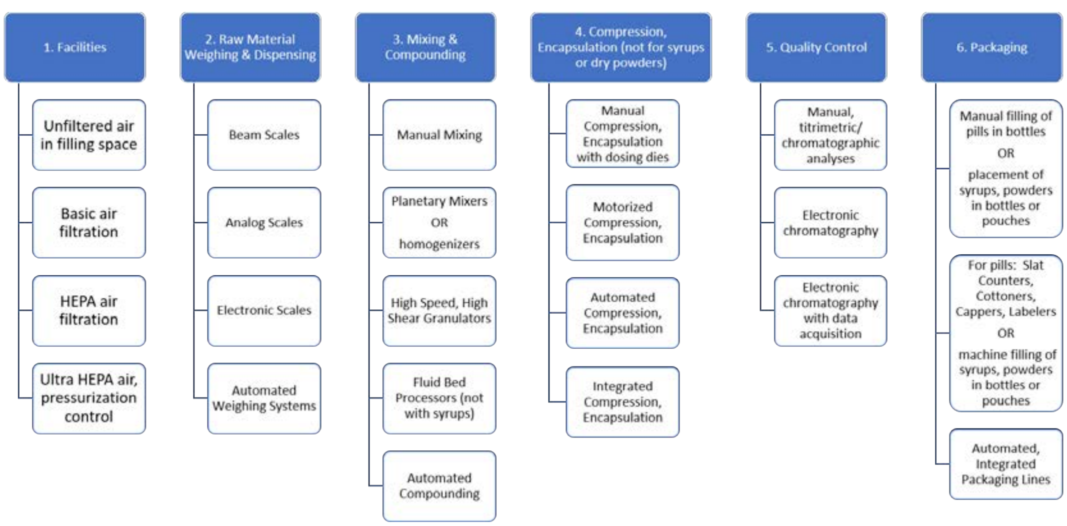


Figure A.8: Pharmaceutical: Business Functions and Technologies

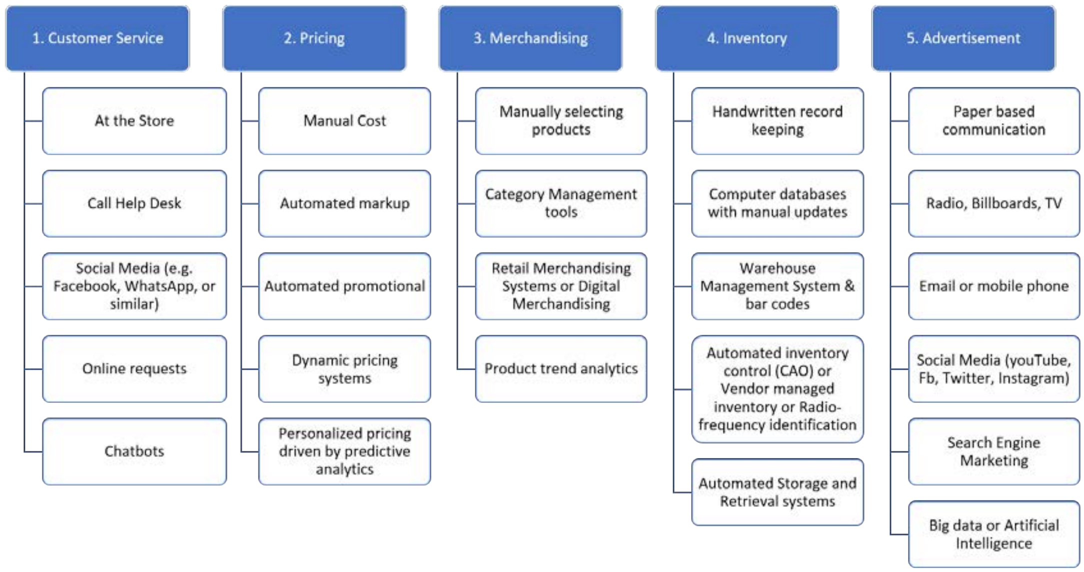


Figure A.9: Wholesale and Retail: Business Functions and Technologies

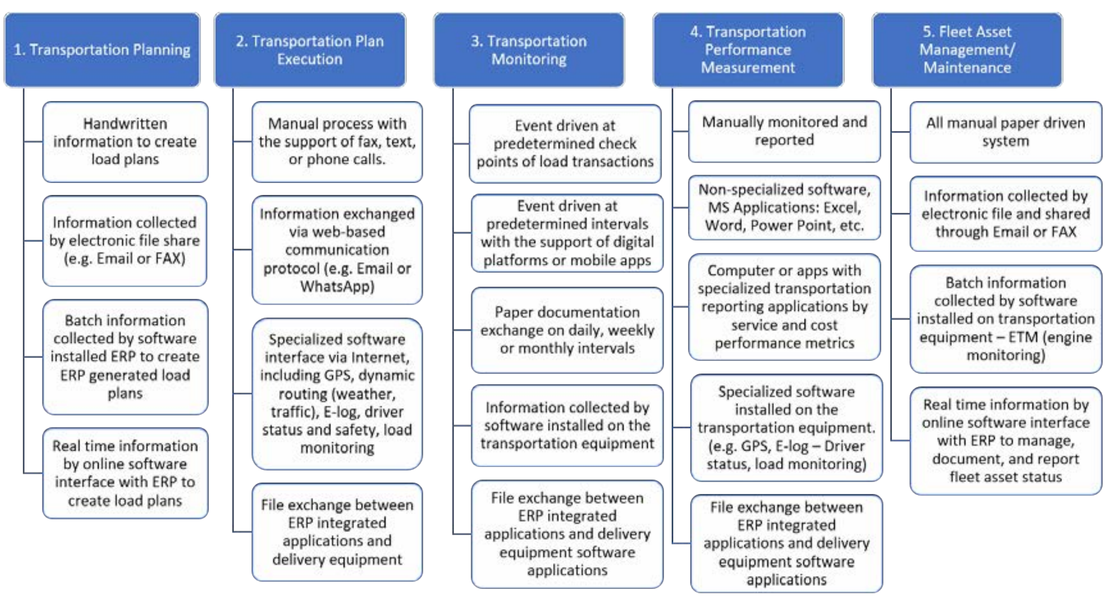


Figure A.10: Land Transportation: Business Functions and Technologies

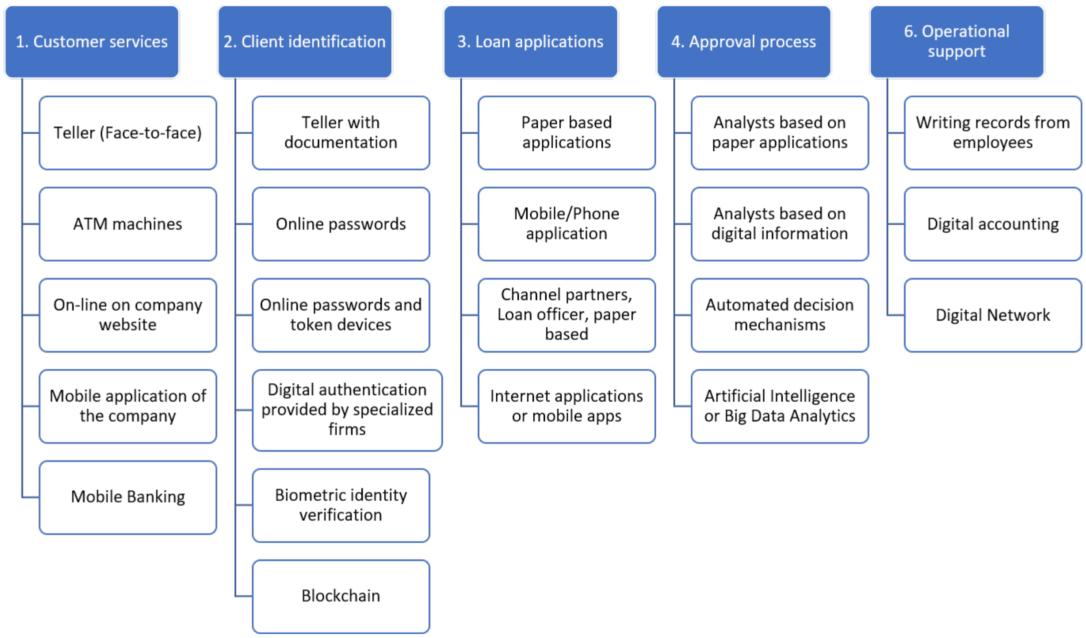


Figure A.11: Financial Services: Business Functions and Technologies

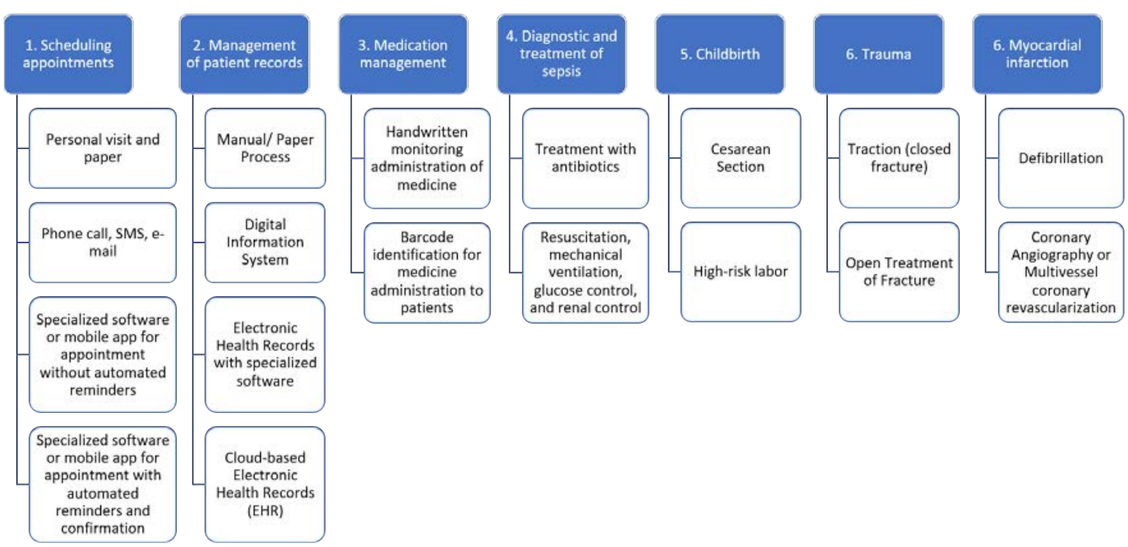


Figure A.12: Health Services: Business Functions and Technologies

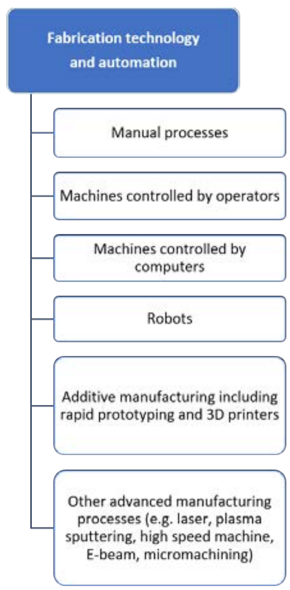


Figure A.13: Other Manufacturing: Business Functions and Technologies

A.2 Sampling frame

The sampling frames for the Brazilian state of Ceará, Senegal, and Vietnam were based on the most comprehensive and latest establishment census available from national statistical agencies or administrative business register. For Brazil, the sampling frame was based on the 2017 *Relação Anual de Informações Sociais* (RAIS). RAIS is an employer-employee administrative registry database managed by the Ministry of Economy (MoE), which covers all Brazilian registered firms with at least one employee. For Senegal, the sampling frame was based on the 2016 *Recensement Général des Entreprises* (RGE) from the *Agence Nationale de la Statistique et de la Démographie* (ANSD), which covers all establishments with a business location operating in Senegal. For Vietnam, the sampling is based on the 2018 Establishment Census from the General Statistical Office (GSO), which covers all registered establishments operating in Vietnam.

The universe of study includes establishment with 5 or more employees in agriculture, manufacturing and services. The sector classification is based on the International Standard Industrial Classification of All Economic Activities (ISIC), Rev. 4. More specifically, our sample includes firms from the following ISIC rev 4 sectors: Agriculture (ISIC 01, from Group A); All manufacturing sectors (Group C); Construction (Group F), Wholesale and retail trade (Group G), Transportation and storage (Group G), Accommodation and food service activities (Group I), Information and communication (Group J), Financial and insurance activities (Group K), Financial services (ISIC, 64), Travel agency (ISIC 79, from group N), Health services (ISIC 86, from group Q), and Repair services (ISIC 95, from Group S).

We exclude micro-firms with fewer than 5 employees. Micro firms, particularly in developing countries, are more likely to be informal (Ulyssea, 2018), making them less likely to be captured in the sampling frame; and this would require further adjustment in the survey instrument and sampling design.[81] This size threshold is aligned with other firm-level standardized surveys with comparability across countries. The World Bank Enterprise Survey (WBES) also uses a threshold of 5 employees. The World Management Survey (WMS) uses a threshold of 50 employees. In the case of Senegal, our sampling frame includes all firms registered in the establishment census of ANSD. The RGE in Senegal has 407,882 businesses, but most of them (82%) refers to individual businesses or self-employees. Firms with 5+ employees represent 6% of total, but they are responsible for about 50% of total employment and 81% of total sales in the RGE database. For Brazil, the RAIS has 85,441 establishments registered in Ceará. Establishments with 5+ employees represent about 39% of total establishments and 93% of total employment.

[81] In addition, establishments below this threshold often lack the organizational structure to respond to some of the questions.

We stratified the universe of establishments by firm size, sector of activity, and geographic regions. Our sample is representative across these dimensions.[82] In the firm size stratification, we have three strata: small firms (5-19 employees), medium firms (20-99 employees), and large firms (100 or more employees). Regarding sector, for all countries, we stratified at least for agriculture (ISIC 01), food processing (ISIC 10), Wearing apparel (ISIC 14), Retail and Wholesale (ISIC 45, 46 and 47), other manufacturing (Group C, excluding food processing and apparel), and other Services (including all other firms, excluding retail). We use this sector structure of the data for most of the analysis in this paper. Additional sector stratification that were country specific included: Motor vehicles (ISIC 29), for Brazil; Leather (ISIC 15), Pharmaceutical (ISIC 21), and Motor vehicles (ISIC 29), for Vietnam; and Land transport (ISIC 49), Finance (ISIC 64), and Health (ISIC 86), for Senegal.[83] In the geographic stratification, we use sub-national regions. In Brazil, we cover only one state, Ceará. In Vietnam, we make 8 geographic strata: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh). In Senegal, we have 7 regional strata including Dakar, Diourbel, Kaolack, Kolda, St. Louis, Thies, and Ziguinchor.

To calculate the optimal distribution of the sample, we followed a similar methodology as described by the World Bank (2009). The sample size for each country was aligned with the degree of stratification of the sample.

A.3 Country samples

Overall, in the case of the state of Ceará, our universe includes 24,288 establishments. We collected data for 711 establishments randomly selected from RAIS. Tables A.1 and A.2 provide the information on the distribution of firms in the population and the sample for Ceará, by size group and sectors.

[82] In Senegal, in order to ensure the representativeness of the sample, we added a fourth dimension of stratification, ANSD's formal status. Unlike Brazil and Vietnam, the census survey from which we build the sampling frame in Senegal includes both formal and informal firms. However, the criteria for formality in Senegal are more stringent than in Brazil or Vietnam and, as a result, many of the informal firms in the Senegal would be classified as formal in the other two countries. Hence, the universes (and samples) are comparable across countries. To be in the sampling frame in Senegal, firms must have at least 5 employees and have a physical address. By having business premises, these establishments are likely to pay at least fees to local governments, which make them comparable with registered firms covered by our sampling frame in Brazil and Vietnam. To be coded as formal, firms in Senegal need to be registered and need to use an accounting system that is compatible with the West African Accounting System (SYSCOA). In contrast, in Brazil and Vietnam the only requisite to be formal is to be registered. All the findings in the paper are robust to restricting the Senegal sample to only formal firms and to using higher thresholds for employment.

[83] These specific stratifications were taken into consideration when determining sampling weights.

Table A.1: Population Distribution, Brazil

Region	Size	Agri-culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Ceará	Small	240	523	788	1699	9255	5362	23351
	Medium	111	220	295	642	1764	1643	
	Large	47	51	54	148	243	266	
Total		398	794	1137	2489	11262	7271	23351

Note: Data from the 2017 *Relação Anual de Informações Sociais* (RAIS), an employer-employee administrative registry database managed by the Ministry of Economy (MoE).

Table A.2: Sampling Distribution, Brazil

Region	Size	Agri-culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Ceará	Small	32	47	51	63	48	47	711
	Medium	24	39	42	52	44	47	
	Large	19	29	31	36	29	31	
Total		75	115	124	151	121	125	711

Note: Data from the Firm-level Adoption of Technology (FAT) survey conducted in Brazil.

In the case of Vietnam our universe includes 179,725 establishments. We collected data on 1,499 establishments randomly selected from the GSO's census. Tables A.3 and A.4 provide the information on the distribution of firms in the population and the sample for Vietnam.

Table A.3: Population Distribution, Vietnam

Region	Size	Agri-culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Region 1	Small	29	91	82	2074	4183	3155	13417
	Medium	12	38	61	1225	491	923	
	Large	4	28	103	623	44	251	
Region 2	Small	39	49	29	691	1270	897	4354
	Medium	10	22	54	408	208	308	
	Large	0	5	60	222	18	64	
Region 3	Small	85	95	46	1001	2330	2547	8572
	Medium	24	31	50	452	327	1042	
	Large	7	27	81	167	31	229	
Region 4	Small	117	78	14	164	539	716	2162
	Medium	28	43	7	70	76	206	
	Large	12	13	7	12	10	50	
Region 5	Small	89	145	127	3699	4278	2978	17942
	Medium	33	101	134	2494	589	798	
	Large	16	100	204	1937	48	172	
Region 6	Small	7	143	31	868	1048	781	4595
	Medium	8	92	46	656	154	253	
	Large	0	54	60	340	13	41	
Region 7	Small	279	669	578	9597	34466	22025	77462
	Medium	35	100	126	1463	2954	3064	
	Large	7	33	90	536	338	1102	
Region 8	Small	204	564	854	7453	18024	11661	51221
	Medium	36	200	433	2364	3376	3445	
	Large	6	111	365	820	469	836	
Total		1087	2832	3642	39336	75284	57544	179725

Note: Data from the 2018 Establishment Census managed by the General Statistical Office (GSO). Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh).

Table A.4: Sample Distribution, Vietnam

Region	Size	Agri-culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Region 1	Small	9	5	5	32	36	28	219
	Medium	3	5	6	30	6	9	
	Large	1	5	6	27	2	4	
Region 2	Small	11	8	8	15	14	11	134
	Medium	3	7	8	11	5	6	
	Large	0	2	8	8	4	5	
Region 3	Small	14	9	9	15	25	27	205
	Medium	8	9	9	13	8	14	
	Large	2	8	10	12	6	7	
Region 4	Small	14	10	4	9	10	12	123
	Medium	8	10	3	6	6	8	
	Large	5	4	2	3	3	6	
Region 5	Small	6	2	2	43	33	23	227
	Medium	6	2	4	40	3	4	
	Large	5	2	3	45	2	2	
Region 6	Small	2	6	6	23	10	8	131
	Medium	2	6	5	22	3	3	
	Large	0	6	6	19	2	2	
Region 7	Small	2	3	4	64	40	40	228
	Medium	3	2	2	17	12	13	
	Large	0	2	2	15	2	5	
Region 8	Small	2	3	4	53	40	40	232
	Medium	2	2	2	25	14	14	
	Large	2	2	2	19	2	4	
Total		110	120	120	566	288	295	1499

Note: Data from the Firm-level Adoption of Technology (FAT) survey in Vietnam. Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh).

For Senegal our universe includes 9,631 establishments. We collected data for 1,786 establishments randomly selected from the RGE-ANSD. Tables A.5 and A.6 provide the information on the distribution of firms in the population and the sample for Senegal.

Table A.5: Population Distribution, Senegal

Region	Size	Agri-culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Dakar	Small	72	273	809	859	1126	979	4930
	Medium	9	75	19	114	125	281	
	Large	9	22	0	48	26	84	
Diourbel	Small	18	84	182	204	214	80	816
	Medium	1	9	1	7	8	5	
	Large	1	1	0	0	0	1	
Kaolack	Small	26	36	242	175	91	50	820
	Medium	50	12	3	18	63	26	
	Large	11	1	0	0	8	8	
Kolda	Small	480	28	74	87	64	51	819
	Medium	21	1	1	1	4	6	
	Large	1	0	0	0	0	0	
St. Louis	Small	125	43	60	116	96	70	688
	Medium	65	3	1	5	21	31	
	Large	41	2	0	1	4	4	
Thies	Small	26	66	229	237	292	217	1207
	Medium	2	14	4	4	33	60	
	Large	6	3	0	1	5	8	
Ziguinchor	Small	50	15	32	74	46	98	351
	Medium	11	1	0	0	7	12	
	Large	1	1	0	0	1	2	
Total		1026	690	1657	1951	2234	2073	9631

Note: Data from the 2016 *Recensement Général des Entreprises* (RGE) from the *Agence Nationale de la Statistique et de la Démographie* (ANSD).

Table A.6: Sample Distribution, Senegal

Region	Size	Agri- culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Dakar	Small	14	48	102	136	160	222	993
	Medium	6	40	8	52	21	89	
	Large	5	16	0	27	17	30	
Diourbel	Small	2	14	15	22	25	7	102
	Medium	1	4	0	4	2	4	
	Large	1	0	0	0	0	1	
Kaolack	Small	3	5	23	19	13	15	133
	Medium	4	3	2	1	7	16	
	Large	9	1	0	0	6	6	
Kolda	Small	54	10	9	11	9	10	124
	Medium	8	1	0	1	4	6	
	Large	1	0	0	0	0	0	
St. Louis	Small	22	11	7	17	8	7	142
	Medium	10	3	1	4	5	11	
	Large	27	2	0	1	3	3	
Thies	Small	3	9	22	31	26	34	162
	Medium	1	5	1	0	3	14	
	Large	4	2	0	0	4	3	
Ziguinchor	Small	11	14	8	18	15	28	130
	Medium	11	1	0	0	7	12	
	Large	1	1	0	0	1	2	
Total		198	190	198	344	336	520	1786

Note: Data from the Firm-level Adoption of Technology (FAT) survey in Senegal.

A.4 Survey Weights

We construct the sampling weights of establishments in two steps. First, we compute design weights as reciprocals of inclusion probabilities. Then, to mitigate the risk of non-response bias, we adjust the design weights for non-response.

We adopt a stratified one stage element sampling design and randomly select establishments with equal probabilities within strata. Therefore, the inclusion probability of establishment k, within stratum isr (identified by industry i, size s, and region r), is:

$$\pi_{isr\ \ k} = \frac{n_{isr}}{N_{isr}} \tag{A.1}$$

where $n_i sr$ is the number of establishments targeted by the survey for stratum isr, and $N_i sr$ is the number of establishments in the sampling frame for the same stratum. Accordingly, the design weights of establishments are:

$$d_{isr\ \ k} = \frac{1}{\pi_{isr\ \ k}} = \frac{N_{isr}}{n_{isr}} \tag{A.2}$$

To adjust the design weights in equation A.2 for non-response we follow a simple Response Homogeneity Groups (RHG) approach (Särndal, Swensson and Wretman, 1992), with the groups determined by the strata. In other words, we assume that establishment response probabilities are the same within each stratum, but differ across different strata. Under the RHG approach assumptions, response probabilities can be estimated using the observed response rates within each group, and bias protection is obtained by dividing design weights by group-level response rates.

Denoting with the estimated response probability in stratum isr, and with $m_i sr$ the number of respondent establishments in the stratum (so that $m_i sr n_i sr$), the non-response adjusted weights can thus be written as follows:

$$w_{isr\ \ k} = \frac{d_{isr\ \ k}}{\hat{\theta_i sr}} = \frac{d_{isr\ \ k}}{m_{isr}/n_{isr}} = \frac{N_{isr}/n_{isr}}{m_{isr}/n_{isr}} = \frac{N_{isr}}{m_{isr}} \tag{A.3}$$

Note that the adjusted weights in equation A.3 are such that the distribution of our respondent sample across strata exactly matches the distribution of establishments in the sampling frame:

$$\sum_{k\ \in R_i sr} w_{isr\ \ k} = N_{isr} \tag{A.4}$$

where $R_i sr$ denotes the respondent sample for stratum isr.

Because of the different number of establishments in each country, when computing global statistics, we re-scale weights so that all countries are equally weighted.

A.5 Descriptive Statistics

Table A.7 provides descriptive statistics for the sample we used in this study. Column (1) presents the overall sample, which is the average of Brazil, Vietnam, and Senegal with the uniform weight. Columns (2) to (4) show the descriptive statistics for each country. Firm-level characteristics include employment, firm age, export, multinational corporation (MNC), and sectors. All estimates are weighted by the sampling weights. We observe that the average and median size of establishments are relatively larger for Brazil and Vietnam, compared to Senegal. Vietnam has a larger share of exporters and foreign owned firms than Senegal and Brazil.

Table A.7: Descriptive Statistics

	(1) Overall	(2) Brazil	(3) Vietnam	(4) Senegal
Employment	38	47	46	22
S.D. of Employment	(209)	(211)	(265)	(125)
P10 of Employment	5	7	5	5
P50 of Employment	12	18	12	8
P90 of Employment	57	74	62	35
Firm Age	15	19	9	16
Export	0.124	0.041	0.169	0.162
Foreign Owned	0.058	0.008	0.120	0.048
Sectors:				
Agriculture	0.044	0.017	0.006	0.110
Food Processing	0.044	0.044	0.016	0.073
Wearing Apparel/Leather	0.084	0.052	0.028	0.172
Moto Vehicle	0.003	0.006	0.002	0.000
Pharmaceutical	0.001	0.000	0.002	0.000
Wholesale & Retail	0.395	0.518	0.419	0.248
Finance	0.003	0.000	0.002	0.007
Land Transport	0.006	0.002	0.002	0.016
Health Service	0.003	0.003	0.003	0.004
Other Manufacturing	0.163	0.102	0.207	0.179
Other Service	0.253	0.256	0.314	0.190

Note: Data from the Firm-level Adoption of Technology (FAT) surveys. Overall is the average of Brazil, Vietnam, and Senegal. Estimates are weighted by the sampling weights. Standard deviation of employment is reported in parenthesis.

A.6 Implementation, quality control, and validation

A critical objective of the project is to obtain robust and comparable measures of the sophistication of technologies used across countries, sectors, and firms. This requires fully harmonized implementation processes across countries, that minimize potential non-response, enumerator, and respondent biases.

Implementation across countries To ensure the accuracy in the responses and the comparability of the data collected across countries, we use a standardized process for implementation across all countries. The same terms of reference are used for the organizations that implement the survey across all countries. These include the requirement that both the organizations, as well as the main team of interviewers, supervisors, and managers, have ample experience on collecting firm-level data in their respective country and follow similar procedures for implementing the survey. We conduct a standard training in each country with enumerators, supervisors, and managers leading the data implementation. The same questionnaire is administered through face-to-face interviews with CAPI in all countries.

The questionnaire is implemented at the establishment level. In the sample, 86% of our observations refer to single establishment firms. In the case of multi-establishment firms, the questionnaire is applied to the specific unit of production that is randomly selected.

Minimizing potential non-response bias Survey implementation is designed to minimize non-response through the use of well-prepared agencies and institutions to administer the survey and the presentation of adequate supporting letters to encourage participation. Table A.8 shows response rates by country, firm size group and sector. Response rates vary between 39% in Brazil (Ceará) and 80% in Vietnam. They are also lower for agriculture and small firms, except for Senegal, where response rates are lower for large firms.

In addition to several actions to minimize unit non-response through the design and implementation of the survey we also have adjusted the sampling weights to minimize response bias. The approach, described in section A.4, guarantees that the weighted distribution of our respondent sample across strata (sector, size, region) exactly matches the distribution of establishments in the sampling frame.

To check the possibility that variation in response rates may lead to biases in the analyses, we implement a series of ex-post tests. First, we study whether, in the sample of contacted firms, there are significant differences between those that responded and those that declined participating or could not be reached. The only information available in all firms we attempted to contact in the three sampling frames is the number of employees. Table A.9 tests whether there are differences in employment between the respondent and

Table A.8: Response rate (by group)

Group	Brazil	Vietnam*	Senegal
Full sample	0.39	0.80	0.57
Size			
Small	0.31	0.89	0.63
Medium	0.36	0.92	0.62
Large	0.37	0.94	0.53
Sector			
Agriculture	0.34	0.85	0.58
Manufacturing	0.35	0.91	0.55
Services	0.44	0.91	0.59

Note: Data from the list of firms contacted by enumerators. Response rates are computed by dividing the number of completed interviews by the number of all contacted firms. (*) For Vietnam, the response rate by size and by sector is based on the original list with 1500 firms, for which the response rate was 90%, reflecting 1346 completed interviews. The GSO provided the overall response rate of 80% for the full sample only disaggregated by region.

non-respondent groups, controlling for characteristics used for stratification. We find no significant differences in firm size between respondents and non-respondents in any of the three countries.

Table A.9: Comparison of firm size between respondents vs non-respondents

VARIABLES	Brazil	Vietnam	Senegal
Respondents (FAT)	2.52	52.34	-4.92
	(22.19)	(80.27)	(6.63)
Observations	1,754	1,500	3,075
R-squared	0.129	0.172	0.237
Controls:			
Sector	$\surd$	$\surd$	$\surd$
Size group	$\surd$	$\surd$	$\surd$
Region	$\surd$	$\surd$	$\surd$

Note: *** p<0.01, ** p<0.05, * p<0.1. Data are from the list of firms contacted by the enumerators. For each country, the level of employment was regressed on a dummy for respondent while controlling for stratification such as sectors, size groups (small, medium, and large), and regions. Estimates for Vietnam are based on the original list of 1500 firms, with 1346 respondents and 154 non-respondents. Robust standard errors in parenthesis.

Second, for Senegal, we explore whether after controlling for observable characteristics, there are significant differences in average technology sophistication in GBFs between firms that required a larger number of attempts to be contacted (top quartile) and those that did not. Table A.10 shows that there are no statistically significant differences in technology sophistication between the two groups.

Table A.10: Comparison of technology sophistication between high and low number of attempts

VARIABLES	Senegal	Senegal
Top quartile of attempts (4 or more)	-0.021	-0.027
	(0.020)	(0.019)
Observations	1,753	1,666
R-squared	0.377	0.437
Controls:		
Sector	√	√
Size group	√	√
Region	√	√
Age		√
Exporter		√
Foreign owned		√

Note: *** p<0.01, ** p<0.05, * p<0.1. Data are from the Senegal FAT survey with information on the number of attempts to complete interview at the firm level. Technology sophistication is regressed on a dummy for the top quartile of the number of attempts (4 or more) with controls for the stratification (sectors, size groups, and regions) and/or firm characteristics (age groups, exporter, and foreign owned). Robust standard errors in parenthesis.

Third, we compare firms that were in the first sample list provided to enumerators and those in subsequent lists. Table A.11 show that there are no statistically significant differences between the two groups.

Fourth, for Brazil, we compare the differences between labor-related indicators from a matched employer-employee administrative data for firms in FAT versus the universe of firms. To perform this comparisons we obtained the weighted average for firms in FAT, using the weights we constructed as described in section A3 and compare it with the average for all firms in RAIS that are part of our universe for the State of Ceará, in Brazil. We then perform a t-test to compare the differences. Table A.12 shows that the differences are not statistically significant.

Minimizing enumerator bias To minimize the potential for enumerators to introduce biases when administering the survey, we conduct in each country standard training and piloting prior to going to the field. The training is led by team members directly involved in the elaboration of the questionnaire. The two to three days training consists of one general presentation about the project, covering the main motivation, relevance, coverage, and protocols that should be used to approach the interviewees and the review of the full questionnaire (question by question). The training material includes pictures of each technology mentioned in the survey both in general and sector-specific business functions, which are

Table A.11: Comparison of technology sophistication between original and replacement sample

VARIABLES	Brazil	Brazil	Vietnam	Vietnam	Senegal	Senegal
Original sample	-0.014	-0.037	0.030	0.043	0.021	0.028
	(0.048)	(0.047)	(0.050)	(0.048)	(0.018)	(0.018)
Observations	638	637	1,484	1,484	1,753	1,666
R-squared	0.299	0.335	0.262	0.320	0.377	0.437
Controls:						
Sector	√	√	√	√	√	√
Size group	√	√	√	√	√	√
Region	√	√	√	√	√	√
Age		√		√		√
Exporter		√		√		√
Foreign owned		√		√		√

Note: *** p<0.01, ** p<0.05, * p<0.1. Data are from the Brazil, Vietnam, and Senegal FAT surveys. For each country, technology sophistication is regressed on a dummy for the original sampling list with controls for the stratification (sectors, size groups, and regions) and/or firm characteristics (age groups, exporter, and foreign owned). Robust standard errors in parenthesis.

shared with enumerators. After going over the full questionnaire and clarifying any questions that emerge, the participants of the training conduct a mock interview using CAPI, under the supervision of our team.

A pilot of the questionnaire is implemented in each country with firms out of the sample. This allows to fine-tune questions to the local language and select the most relevant examples in each question. After the pilot, our teams have the opportunity to discuss with the managers implementing the questionnaires and clarify any potential question over the implementation process. A similar check happens after 10% of data collection and contin-

Table A.12: Comparison between FAT sample and RAIS data (universe)

	Number of employees	Average wage	Share college	Share low-skill	Share high high-skill
FAT Average (weighted)	28.55	1,311.89	0.05	0.16	0.42
RAIS Average (universe)	23.85	1,349.29	0.05	0.17	0.39
Estimate (RAIS - FAT)	-4.70	37.40	0.00	0.00	-0.03
Standard Error	(3.08)	(29.77)	(0.01)	(0.01)	(0.02)
T-Statistic	-1.52	1.26	0.55	0.20	-1.64

Note: *** p<0.01, ** p<0.05, * p<0.1. Data from the 2017 *Relação Anual de Informações Sociais* (RAIS) and the Firm-level Adoption Technology (FAT) survey in Brazil. The estimates from RAIS data are unweighted, and those from FAT surveys are weighted by the sampling weights. Robust standard errors in parenthesis.

ues across the implementation. The use of CAPI allows to include logical conditions and skips that reduce the potential for abnormal values or non-response to specific questions. We conduct ex-post tests on the differences in sophistication in abnormal interviews by running regressions of firm-level sophistication on enumerator dummies and firm controls as discussed in the text. Table A.13 shows that enumerator dummies are not significant for Brazil. For Senegal and Vietnam, less than 10% of enumerator dummies are statistically significant. Table A.14 compares the average technology sophistication (GBF) excluding the firms with abnormal enumerators and in the entire sample. We find no economic or statistical difference between mean sophistication in both samples in either Senegal or Vietnam.

Table A.13: Analysis of enumerator bias

VARIABLES	Brazil	Vietnam	Senegal
Share of Significantly Different Interviewers	0.00	0.09	0.08
Number of Significantly Different Interviewers	0	13	2
Number of Interviewers	8	145	25

Note: Data from the Firm-level Adoption of Technology (FAT) surveys in Brazil, Vietnam, and Senegal. Significantly different interviewers are identified from the regressions of employment on interviewer dummies with controlling for stratification information (e.g., sector, size, and region). For each country, the share of significantly different interviewers is computed by dividing the number of interviews conducted by significantly different interviewers by the total number of interviews.

Table A.14: Difference in technology sophistication in general business functions with and without outlying enumerators

	All Sample	Sample Without Different Enumerators	Difference
Vietnam			
Mean	1.934	1.947	-0.013
SE	(0.012)	(0.012)	(0.017)
Observations	1,499	1,341	
Senegal			
Mean	1.406	1.404	0.002
SE	(0.011)	(0.011)	(0.016)
Observations	1,786	1,784	

Note: *** p<0.01, ** p<0.05, * p<0.1. Data from the Firm-level Adoption of Technology (FAT) surveys in Vietnam and Senegal. Brazil is excluded because it does not include significantly different interviewers. The average of technology sophistication in general business functions is compared between all sample and sample excluding significantly different enumerators. Standard errors in parenthesis.

Minimizing respondent bias The survey in these three countries was administered through face-to-face interviews with CAPI. A multidisciplinary literature has emphasized that face-to-face is often more accurate than alternative modes.[84] The advantage of face-to-face interviews is greater in a long questionnaire such as FAT, where interviews lasted from between 35 minutes to one hour. Naturally, the disadvantage of face-to-face interviews is its higher cost.

A critical factor to minimize respondent bias is to identify the right respondent (Bloom and Van Reenen, 2010). The protocol for the implementation of the survey required that the survey should be ideally answered by the top manager. About 47% of the survey was answered by the owner or CEOs, while the other responses included factory managers, other managers, administrative staff, and accountants. Almost 80% of the interviews were conducted through one visit in person interview with the main respondent. In circumstances in which the main respondent did not have all the information about a general topic of the questionnaire, especially in modules B and C, they were requested to consult with other colleagues.

RAIS validation exercise One of the ex-post checks we conduct in Brazil takes advantage of the fact that we have access to the RAIS administrative data which is a matched employer-employee dataset that covers the universe of firms in the sampling frame. This allows us to compare variables in RAIS with variables we collected in FAT for the same firms. Table A.15 reports the point estimates of regressing firm-level FAT variables on the log or average wages per worker from RAIS and a set of firm-level controls. The FAT variables are log of value added per worker (column 1), and average technology sophistication (GBF, column 2, and SSBF, column 3). In all three cases we find strong positive associations between the FAT and the RAIS variables.

[84] For example, Holbrook, Green and Krosnick (2003) use data from three experiments in the US and show that telephone respondents are less likely to cooperate and more likely to present themselves in socially desirable ways. Jackle, Roberts and Lynn (2006) show in a designed experiment that evaluate the differences between the two modes of data collection that telephone respondents are more likely to give socially desirable responses, which in our context is likely to result in an upward bias of technology use.

Table A.15: Relationship between FAT survey variables and log of wages from administrative data for Brazil

Variable	(1) ln(VAPW)	(2) GBF	(3) SSBF
ln(Wage) RAIS	0.873***	0.507***	0.549***
	(0.200)	(0.121)	(0.138)
Observations	530	675	568
R-squared	0.217	0.354	0.230
Controls:			
Sector FE	√	√	√
Region FE	√	√	√
Size group	√	√	√
Age	√	√	√
Exporter	√	√	√
Foreign owned	√	√	√

Note: *** p<0.01, ** p<0.05, * p<0.1. Average wage information for each establishment is obtained from the 2017 *Relação Anual de Informações Sociais* (RAIS) merged with the Firm-level Adoption of Technology (FAT) data used in this exercise, including value added per worker (VAPW), the technology adoption indices (GBF and SSBF), and firm characteristics used as controls. Robust standard errors in parenthesis.

B Results referred to in Section 3

This section contains the results referred to in section 3 not included in the main text of the paper. First, we present the analysis of the LMA curves. Then, we report the skewness of the distributions of projected productivity on firm sophistication for each value of ϕ show the ro

B.1 LMA Curves

This section provides the results for the line of independence minus absolute concentration (LMA) curves. The LMA curve is the vertical difference between two curves. The first curve is the absolute concentration curve of a variable X (e.g., firm size) given the technology sophistication s_j under the assumption that the two variables are statistically independent. The second curve is the absolute concentration curve of X as a function of the cumulative distribution $F(s_j)$. The LMA curves allow us to examine the robustness of the association between observable characteristics and cardinalizations of ordinal variables (Schroeder and Yitzhaki, 2017). If the LMA curve does not intersect the horizontal axis, it is impossible to change the sign of the association by means of a monotonic increasing transformation of technology sophistication. When exploring the association of sophistication and firm characteristics, we check that the LMA condition holds. Therefore, the sign of the association between sophistication and firm characteristics is robust to the cardinalization of the sophistication rankings.

We plot the LMA curves for each technology sophistication aggregated measure we used across the paper: ABF (Figure B.1), GBF (Figure B.2), and (Figure B.3). For each technology sophistication measure we estimate the LMA curves with respect to the log of value added per worker, number of employees, sector, and region. The last three variables captures information used in the stratification (size, sector, and region). The results show that LMA curves do not intersect the horizontal axis, which is a sufficient condition for the robustness of signs (Schroeder and Yitzhaki, 2017).

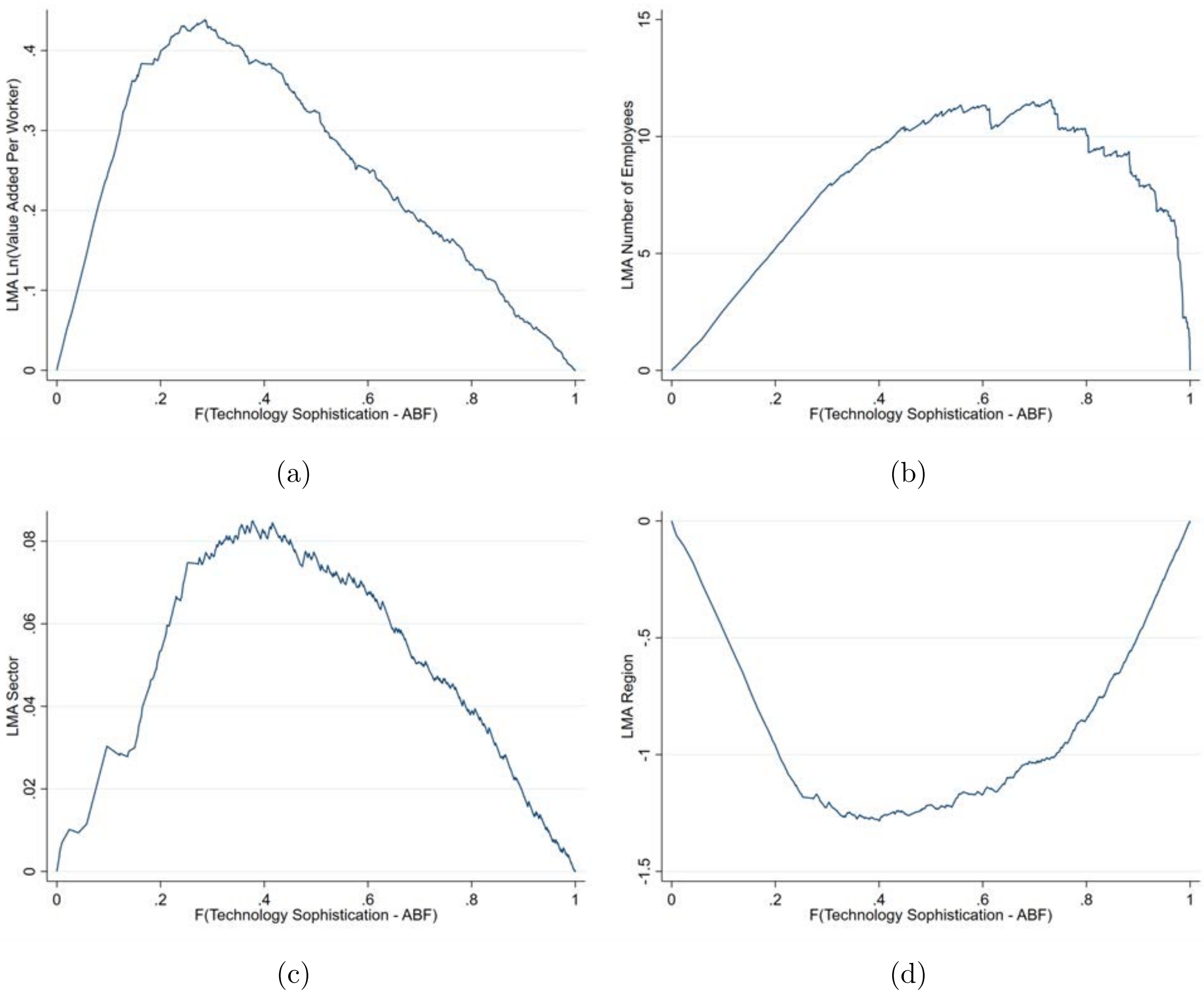


Figure B.1: LMA Curves between Firm Characteristics and Technology Sophistication - ABF

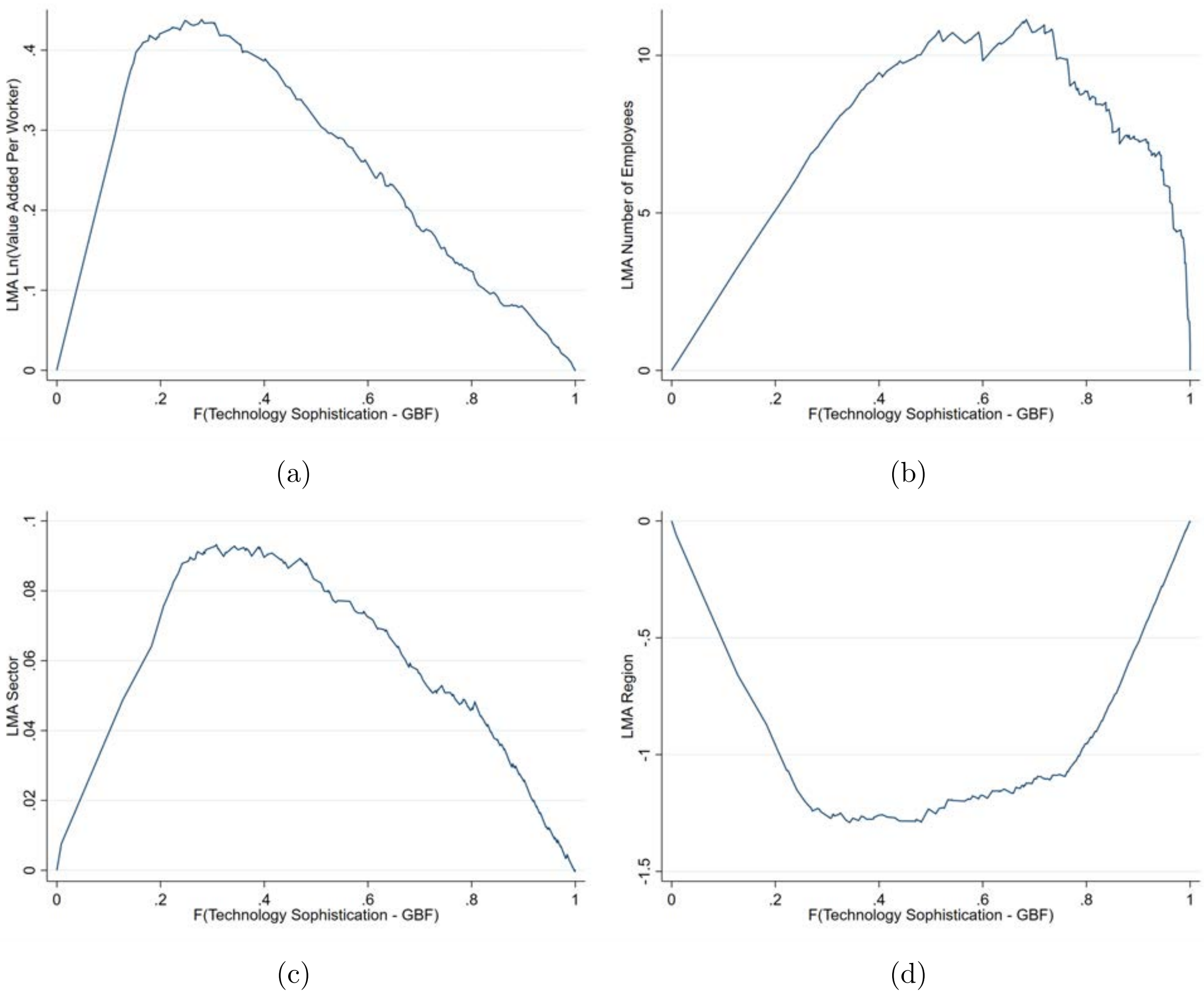


Figure B.2: LMA Curves between Firm Characteristics and Technology Sophistication - GBF

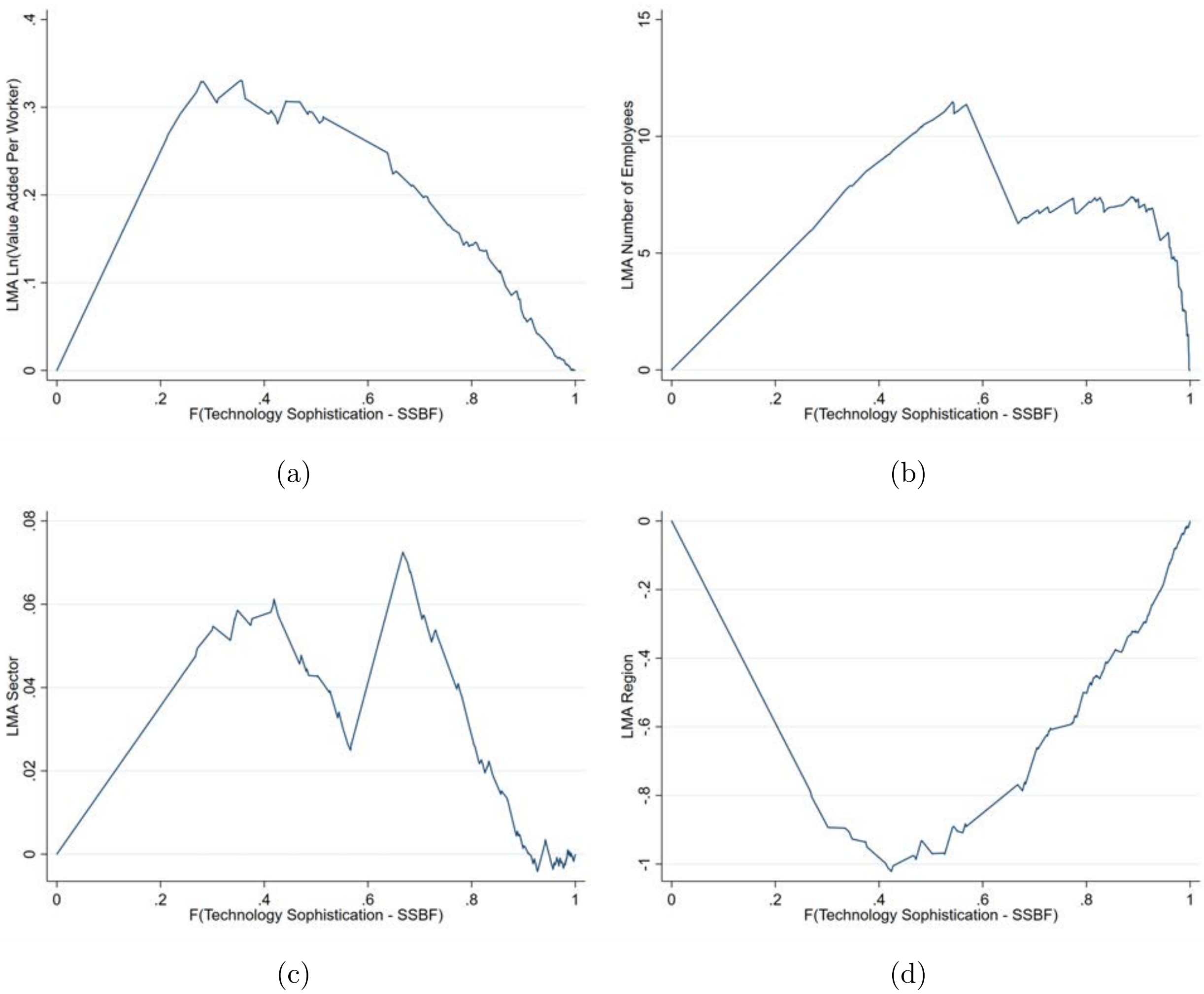


Figure B.3: LMA Curves between Firm Characteristics and Technology Sophistication - SSBF

B.2 Skewness of distribution of projected productivity

To compute the skewness of the distribution of projected productivity we proceed as follows. We regress log firm-level productivity (nominal value added per worker) on firm characteristics, sector, and country dummies. We compute the residual from this regression, and denote it as residual productivity. The skewness of the distribution of residual productivity is reported in the first row of Table B.1. For any given value of ϕ, we regress average firm sophistication s_j^ϕ on firm characteristics, sector, and country dummies. We denote the residual from this regression as residual sophistication. We regress residual productivity on residual sophistication, and compute the forecast from this regression. This is the projection of firm productivity on firm sophistication. We compute the skewness of the distribution of these forecasts. Rows 2-8 of Table B.1 report the skewness for each value of ϕ. The skewness of the distribution of firm productivity falls in between the skewness of the distributions of projected productivity for $\phi = 2/3$ and $\phi = 1$.

Table B.1: Empirical Distribution of Productivity by Technology Sophistication

	Skewness
ln(VAPW) Partialling Out Observables	0.27
Predicted ln(VAPW) on Sophistication $s_{f,j}$ across ϕ:	
$\phi = 1/3$	-0.04
$\phi = 1/2$	0.06
$\phi = 2/3$	0.18
$\phi = 1.0$	0.41
$\phi = 1.5$	0.69
$\phi = 2.0$	0.91
$\phi = 3.0$	1.31

Note: Estimates are weighted by the sampling weights. We partialed out the effects of observables (firm size, firm age, foreign owned, exporting, sector, and country) on ln(VAPW).

B.3 Correlation with off-the-shelf proxies

Table B.2 reports the pairwise correlations between the technology sophistication measures and firm proxies for the use of advanced technologies after partiallying out country (e.g., Brazil, Vietnam, and Senegal) and aggregated sector (e.g, Agriculture, Manufacturing, and Services) dummies.

Table B.2: Pairwise Correlation: Technology Sophistication and Firm Characteristics

	s_j
Size	0.21***
Export	0.28***
Foreign-owned	0.29***
% of professionals	0.25***
% of workers with college degree	0.21***
% of workers with engineering or graduate degree	0.24***
Any R&D	0.25***
Ln(average wage)	0.12***
Ln(average wage), RAIS†	0.36***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The pairwise correlations between technology sophistication and each proxy variable for the use of advanced technologies is estimated after partialling out country and sector dummies (Agriculture, Manufacturing, and Services). Estimates are weighted by the sampling weights. † The *Relação Anual de Informações Sociais* (RAIS) is available only for Brazil.

C Results referred to in Section 4

C.1 Stochastic dominance Analysis

In section 4.2 we perform non-parametric tests to check differences in the distribution of the technology indices across country and sector distributions. This section provides additional results comparing the cross-firm distributions of technology sophistication across countries. We start by looking at the cumulative distribution functions (CDFs) of the technology sophistication (s_j) indices across countries and then examine the Kolgomorov-Smirnoff (KS)-based multiple test results to measure stochastic dominance of distribution across all the combinations of two countries.

The KS-based multiple test, introduced in Goldman and Kaplan (2018), defines its null hypothesis as follows:

$$H_{0r} : F(k) = G(k) \tag{C.1}$$

where $F(\cdot)$ is the first country's CDF for a value of k and $G(\cdot)$ is the second country's CDF. It tests whether CDFs of two countries are the same for each value of k in the domain of the sophistication measure. Because of the "multiple testing problem" that make type I error larger than the desired level, the KS-based multiple testing uses a strong "family wise error rate" (FWER). For example, if FWER is at 5% level, there is no false positives for 95% of the time. We, thus, provide the ranges of k where the null is rejected in the dotted black line of the X-axis panels (b) to (d).

In Figure C.1, we examine the CDF of technology sophistication for ABF and conducts KS-based multiple tests using all sample. Then, we conduct the same analysis for GBF in Figure C.2 and SSBF in Figure C.3. Finally, we examine stochastic dominance of technology sophistication in four sub sectors: Agriculture - Crops in Figure C.4, Food Processing in Figure C.5, Wearing Apparel in Figure C.6, and Wholesale and Retail in Figure C.7. The bold lines at the bottom of the figures show the ranges of stochastic dominance. All results show restricted stochastic dominance of Brazil to Vietnam, Brazil to Senegal, and Vietnam to Senegal.

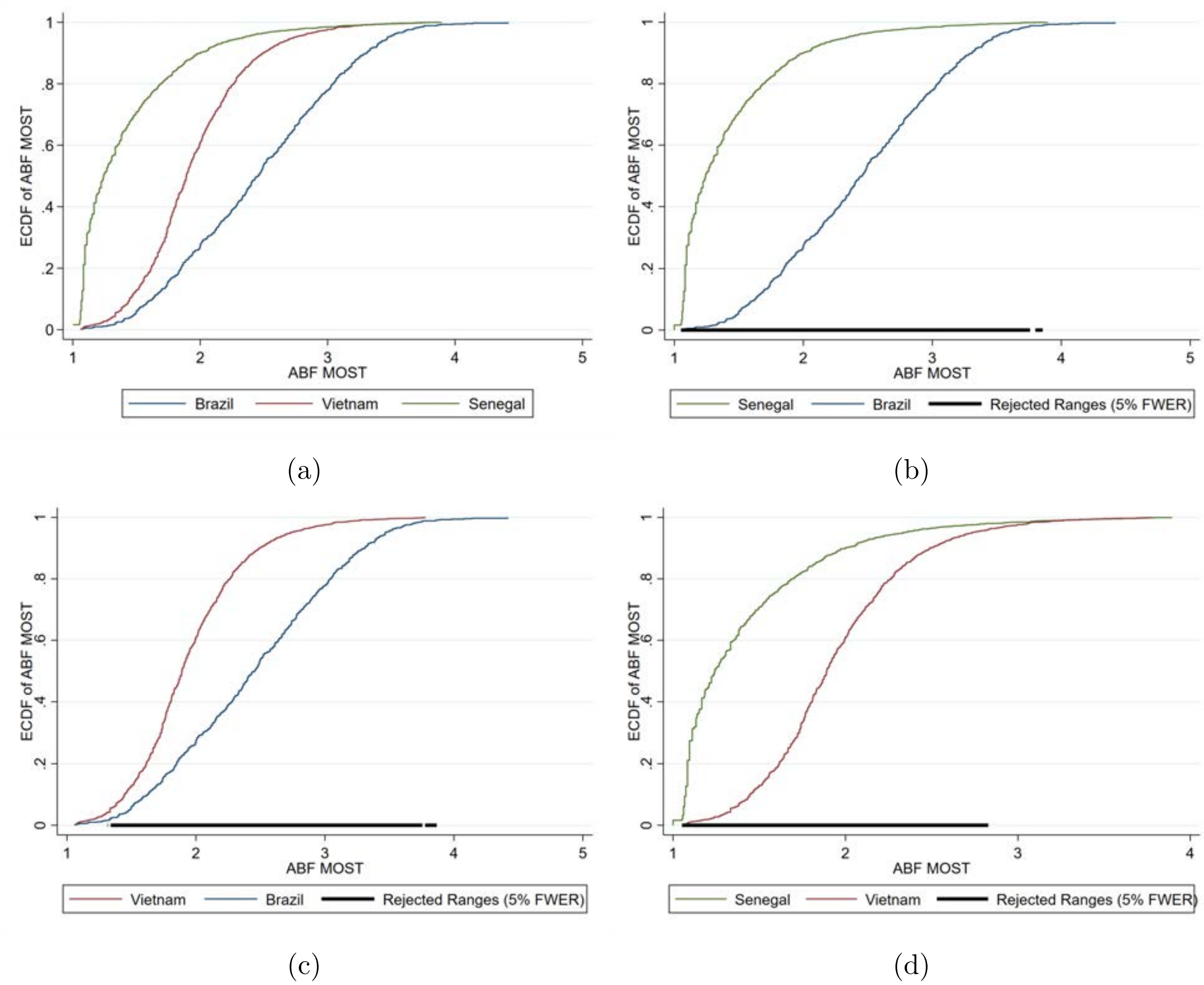


Figure C.1: CDF of Technology Sophistication with the KS based Multiple Tests

Note: The ABF MOST technology index (s_j) is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d). The rejected ranges in Panel (b) is [1.74, 4.70], which covers 97% and 96% of firms in Brazil and Vietnam, respectively. The range [1.10, 4.70] in Panel (c) covers 98% of firms in both Brazil and Senegal. The rejected range [1.08, 3.97] in Panel (d) covers 95% and 97% of firms in Vietnam and Senegal, respectively.

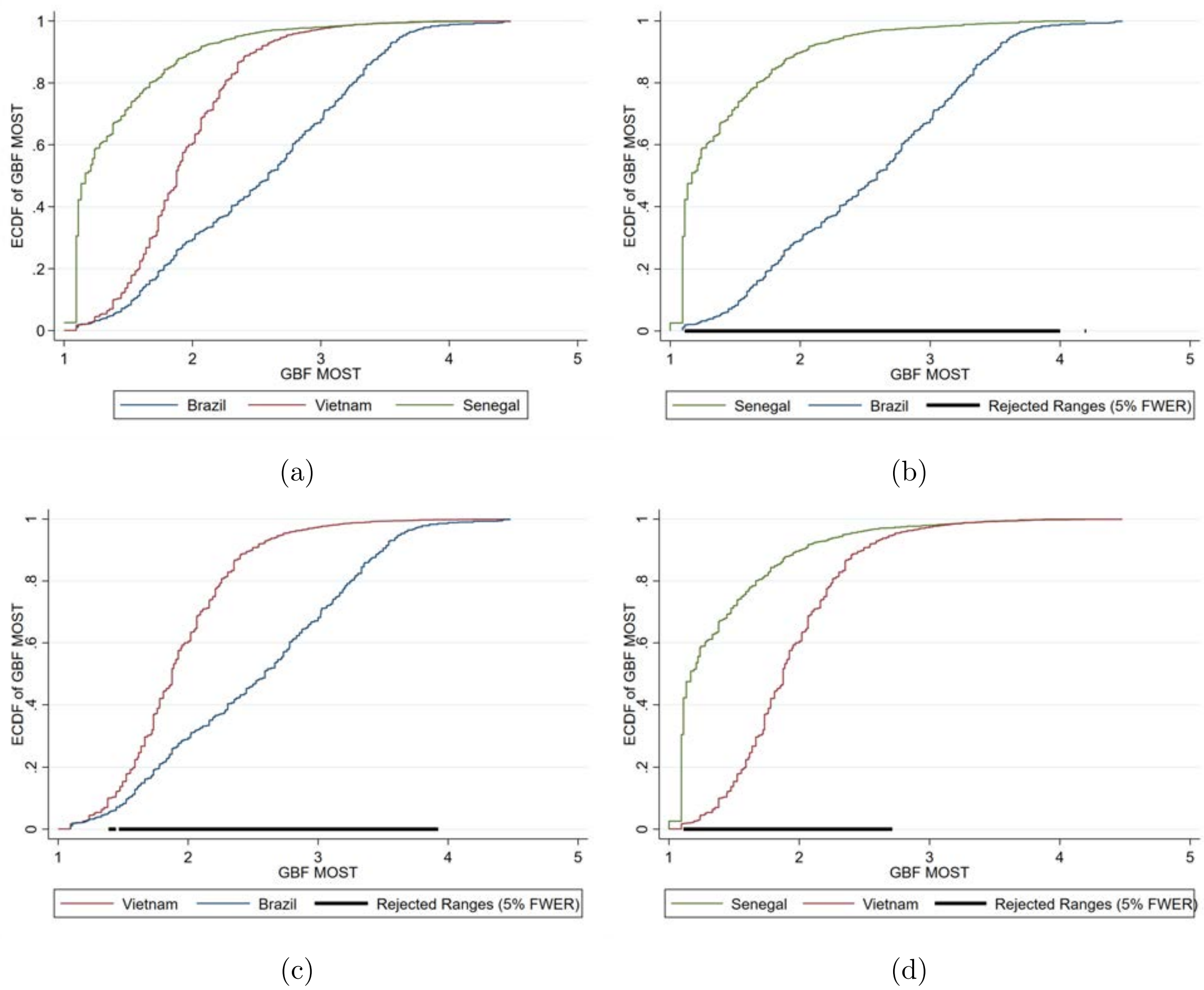


Figure C.2: CDF of General Technology Sophistication (s_j^{GBF}) with the KS based Multiple Tests

Note: The GBF MOST technology index is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d).

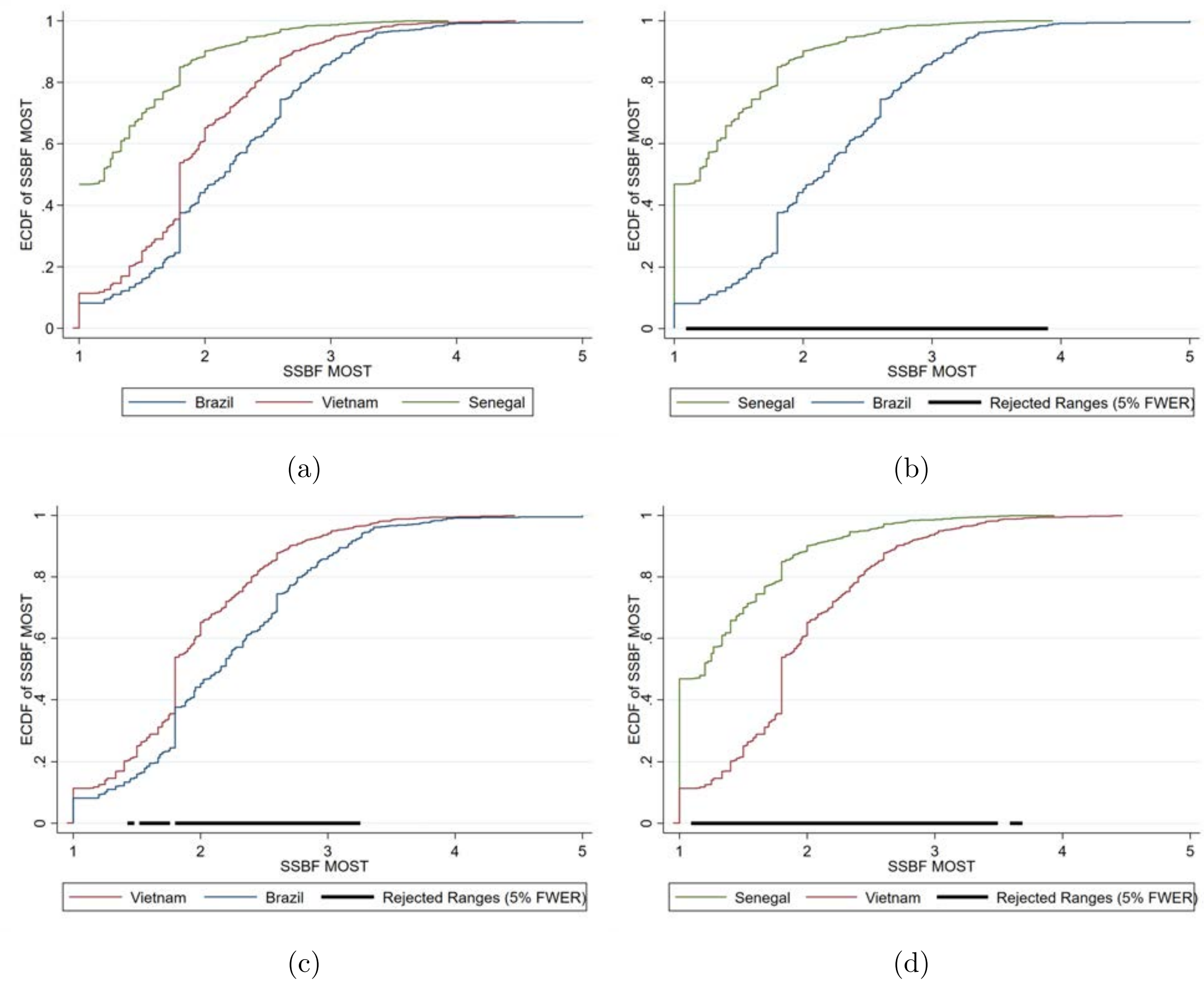


Figure C.3: CDF of Sector-specific Technology Sophistication (s_j^{SSBF}) with the KS based Multiple Tests

Note: The SSBF MOST technology index is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d).

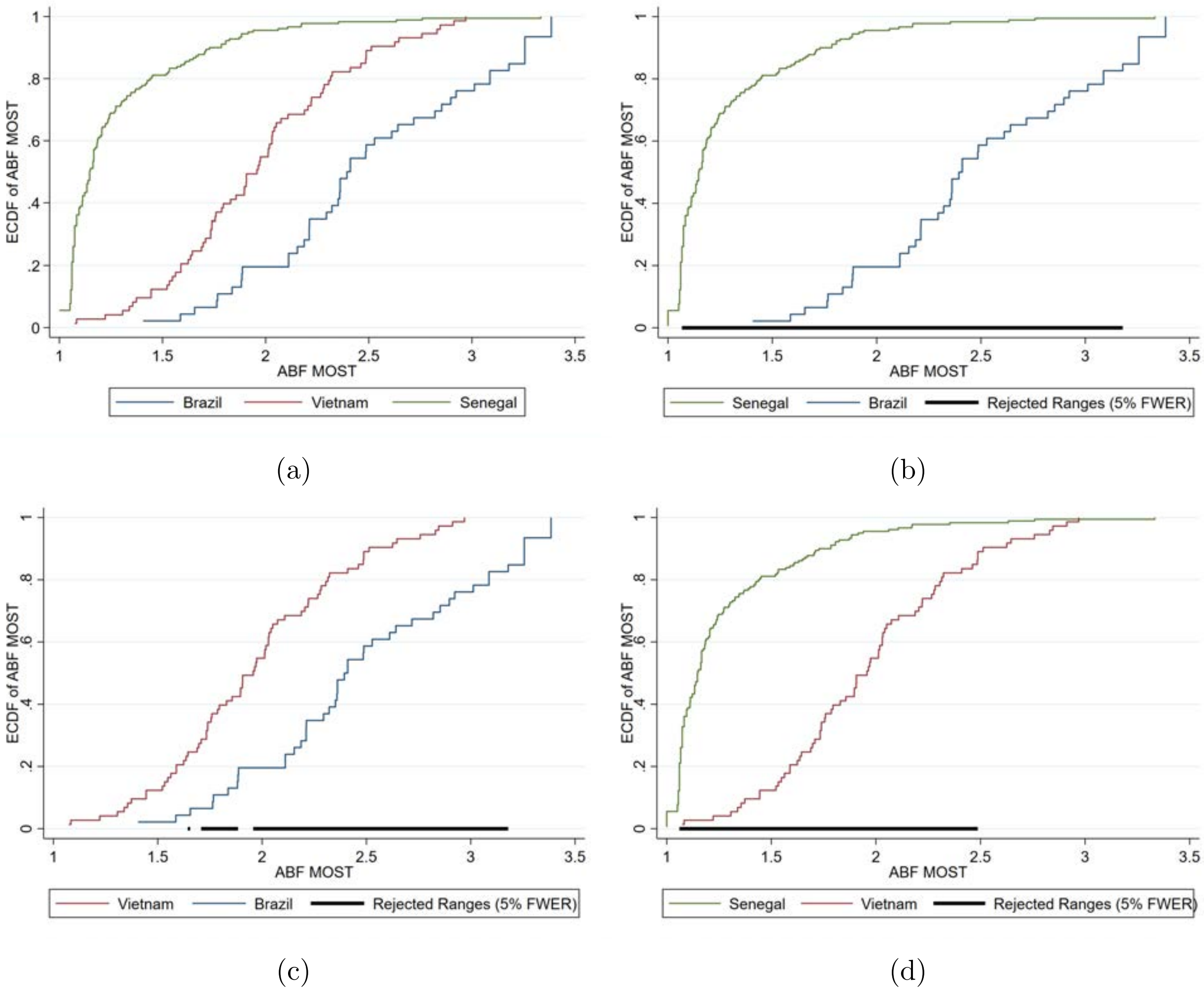


Figure C.4: CDF of Technology Sophistication (s_j) with the KS based Multiple Tests, Agriculture

Note: The sector is restricted to Agriculture. The ABF MOST technology index is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d).

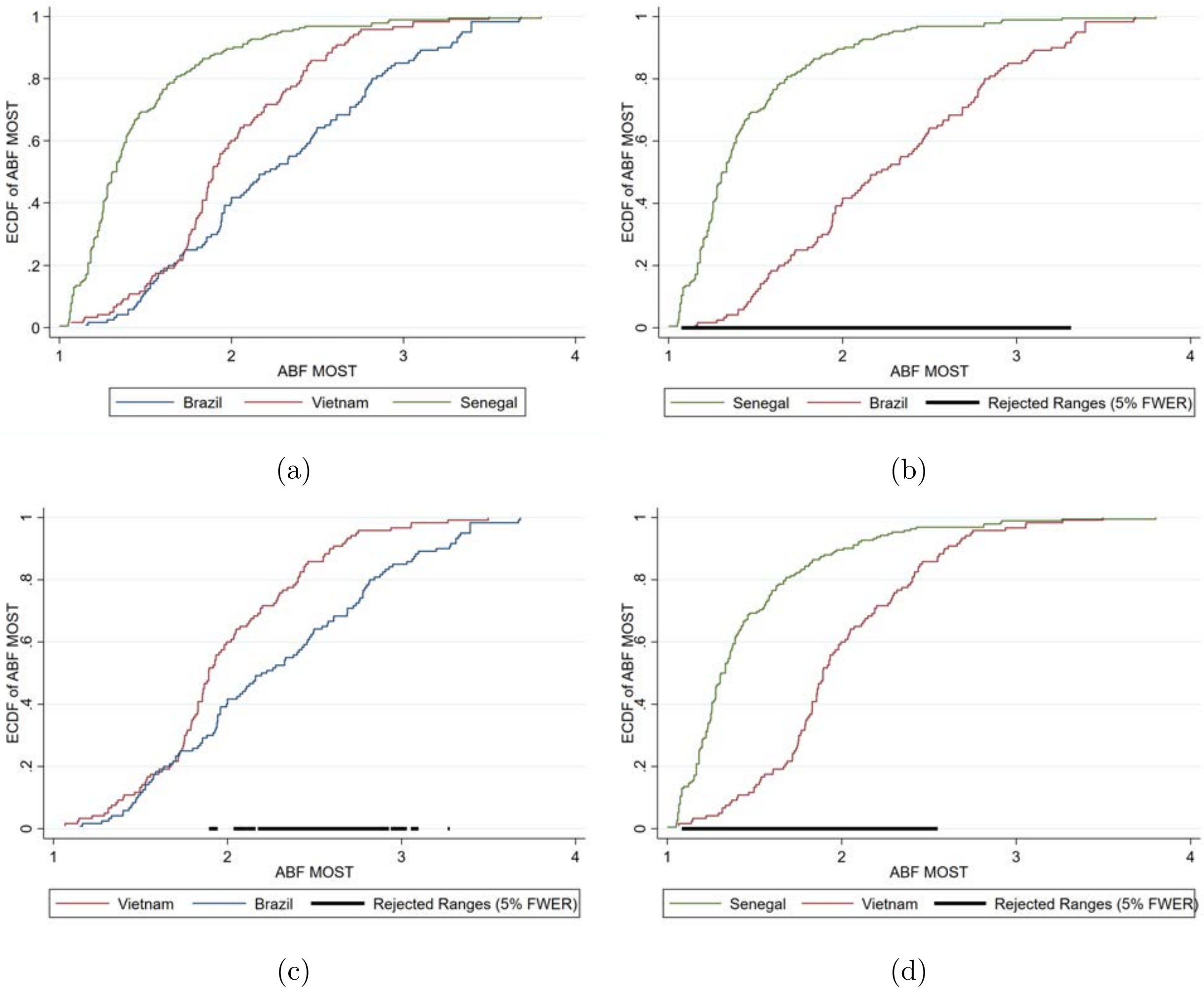


Figure C.5: CDF of Technology Sophistication (s_j) with the KS based Multiple Tests, Food Processing

Note: The sector is restricted to Food Processing. The ABF MOST technology index is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d).

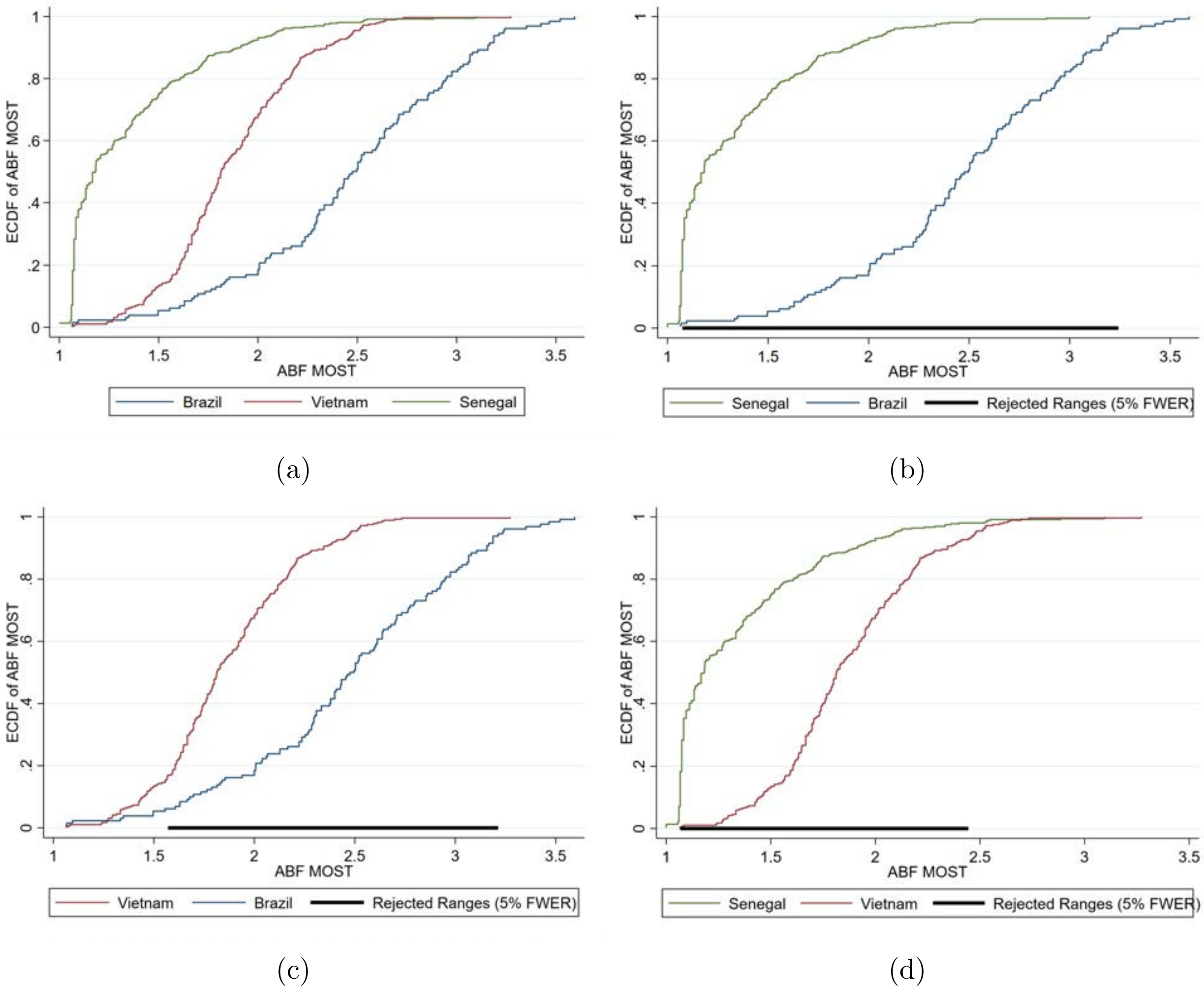
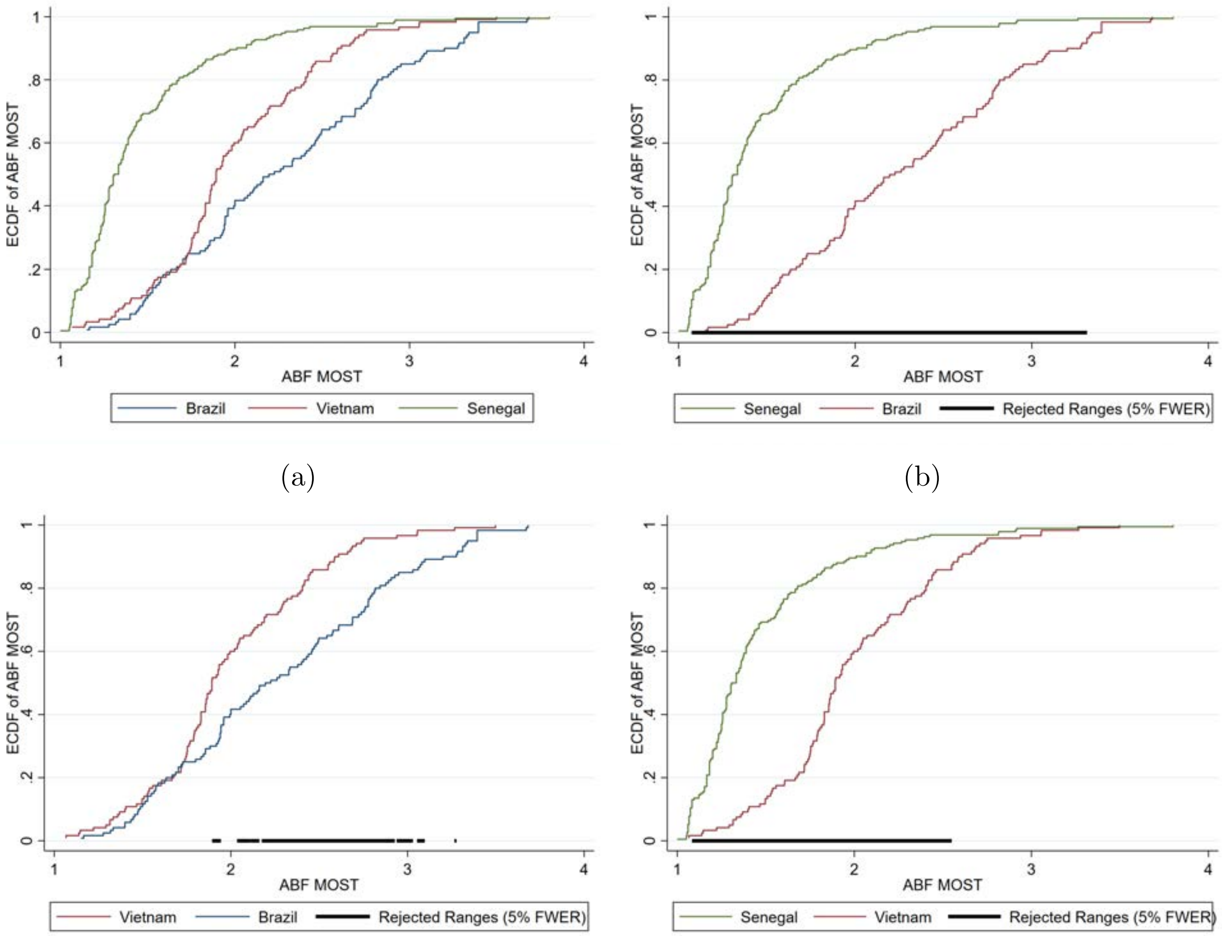


Figure C.6: CDF of Technology Sophistication (s_j) with the KS based Multiple Tests, Wearing Apparel

Note: The sector is restricted to Wearing Apparel. The ABF MOST technology index is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d).



(a)

(b)

(c)

(d)

Figure C.7: CDF of Technology Sophistication (s_j) with the KS based Multiple Tests, Wholesale and Retail

Note: The sector is restricted to Wholesale and Retail. The ABF MOST technology index is used for technology sophistication. The modified Kolmogorov Smirnov test results for CDF values in two distributions are provided as bold lines in the bottom of Panel (b), (c), and (d).

C.2 Regional-level analysis

This section describes how we examine the relationship between technology and regional productivity in Figures 4, 6, and 7 of subsection 4.2. Because all three surveys are stratified by region,[85] regional aggregates of our technology measures are representative. Using the sampling weights, we compute the average level, cross-firm variance, and average within-firm variance in the region for the three broad classes of business functions: average (ABF), general (GBF) and sector-specific (SSBF).

Unfortunately, there are no series for regional GDP in Senegal and Vietnam. To overcome this challenge, we take advantage of the fact that our sample is representative at the regional level, and use firm-level information on value added per worker to estimate regional labor productivity from the data set. Specifically, we estimate the following equation:

$$ln(VAPW)_{j,g,r} = \sum_{g} \beta_g G_g + \sum_{r} \beta_r R_r + \epsilon_{j,g,r} \tag{C.2}$$

where $ln(VAPW)_{j,g,r}$ is the log of value added per worker in firm j, in sector g in region r, R_r is a dummy variable for region r, and G_g is a dummy for each disaggregated sector that captures the heterogeneity in industry composition across regions. The regression is weighted by the sampling weight. The estimate of region's r productivity level is given by the coefficient β_r.

We examine the relationship between average technology sophistication and productivity at the regional-level by estimating the following specification:

$$S_r = \mu + \delta * ln(VAPW)_r + \eta_r \tag{C.3}$$

where S_r is average technology sophistication in region r and $ln(VAPW)_r$ is regional labor productivity.

Table C.1 presents the results of the regressions showing the association between regional technology sophistication and productivity. For technology sophistication measures, we use the average technology sophistication, cross-firm variation in technology, and the average of within-firm variance of technology sophistication.

Table C.2 shows the robustness of the findings on how the sophistication gaps between rich and poor countries vary across sectors when we use regional average sophistication measures instead of country-level average sophistication measures. Table C.3 presents that the results from cross-country/cross-firm variation are robust when we use region instead of country.

[85] The state of Ceará in Brazil is considered one region.

Table C.1: Regional Technology Sophistication and Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Avg of s_j			Var_r			Avg. of $WVar_j$	
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Regional Productivity	0.23***	0.24***	0.20***	0.11***	0.12***	0.03***	0.03***	0.04***	0.05***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	16	16	16	16	16	16	16	16	16
R-squared	0.81	0.75	0.84	0.60	0.57	0.27	0.36	0.29	0.55

Note: *** p < 0.01, ** p< 0.05, * p <0.1. The observation is sub-region within each country. The cross-firm variance of technology in each region is regressed on regional productivity, which is the log of value-added per worker in each region controlling for disaggregated sector dummies. Robust standard errors in parentheses.

Table C.2: Cross-Region Average Technology Sophistication by Sector

	ABF			GBF			SSBF		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.73	1.59	1.60	1.54	1.60	1.63	2.03	1.49	1.53
BR, Ceara	2.52	2.12	2.38	2.32	2.16	2.60	2.81	1.92	1.89
VT, Region 4	2.20	1.91	1.75	1.96	1.91	1.74	2.49	1.84	1.96
VT, Region 7	2.05	1.81	1.99	1.67	1.82	2.00	2.69	1.67	1.95
VT, Region 6	2.04	1.82	1.77	1.67	1.84	1.77	2.78	1.69	1.74
VT, Region 8	2.03	1.82	1.92	2.06	1.87	1.92	1.63	1.56	1.91
VT, Region 1	2.02	1.94	1.93	1.79	1.98	1.95	2.36	1.73	1.80
VT, Region 5	1.97	1.96	1.68	1.75	2.00	1.72	2.29	1.68	1.57
VT, Region 2	1.82	1.82	1.76	1.50	1.83	1.73	2.40	1.64	1.92
VT, Region 3	1.81	1.80	1.76	1.49	1.82	1.77	2.45	1.65	1.66
SN, Dakar	1.66	1.31	1.45	1.39	1.27	1.46	2.09	1.32	1.32
SN, Thies	1.46	1.20	1.24	1.30	1.16	1.26	1.69	1.20	1.20
SN, St. Louis	1.37	1.20	1.34	1.18	1.19	1.36	1.58	1.16	1.20
SN, Diourbel	1.31	1.23	1.23	1.10	1.22	1.25	1.60	1.17	1.20
SN, Kaolack	1.18	1.21	1.15	1.13	1.16	1.17	1.28	1.23	1.05
SN, Kolda	1.14	1.14	1.12	1.11	1.13	1.13	1.20	1.13	1.01
SN, Ziguinchor	1.13	1.22	1.19	1.15	1.20	1.21	1.14	1.17	1.04
GAP: Ceara - Ziguinchor	1.39	0.90	1.19	1.17	0.96	1.39	1.67	0.75	0.85
Relative Gap**	35%	23%	30%	29%	24%	35%	42%	19%	21%

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. Overall is the average of Brazil, Vietnam, and Senegal. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh). Relative gap is the difference between Ceara in Brazil and Kolda in Senegal relative to the maximum technology gap of 4 ($(Brazil - Senegal)/Maximum\ Gap$ (4)). Technology measures are weighted by the sampling weights.

Table C.3: Cross-Firm Variance in Technology Sophistication, Region

	ABF	GBF	SSBF
$Var(S_r - S)$	0.18	0.25	0.09
$Var(s_j - S_r)$	0.20	0.25	0.26
$Var(s_{j,BR-Ceara} - S_{BR-Ceara})$	0.36	0.48	0.38
$Var(s_{j,SN-Dakar} - S_{SN-Dakar})$	0.18	0.20	0.21
$Var(s_{j,SN-Diourbel} - S_{SN-Diourbel})$	0.04	0.04	0.10
$Var(s_{j,SN-Kaolack} - S_{SN-Kaolack})$	0.02	0.02	0.09
$Var(s_{j,SN-Kolda} - S_{SN-Kolda})$	0.01	0.01	0.06
$Var(s_{j,SN-SaintLouis} - S_{SN-SaintLouis})$	0.11	0.10	0.26
$Var(s_{j,SN-Thies} - S_{SN-Thies})$	0.06	0.06	0.17
$Var(s_{j,SN-Ziguinchor} - S_{SN-Ziguinchor})$	0.05	0.06	0.07
$Var(s_{j,VT-Region1} - S_{VT-Region1})$	0.13	0.14	0.21
$Var(s_{j,VT-Region2} - S_{VT-Region2})$	0.17	0.19	0.28
$Var(s_{j,VT_Region3} - S_{VT_Region3})$	0.10	0.12	0.19
$Var(s_{j,VT_Region4} - S_{VT_Region4})$	0.10	0.11	0.31
$Var(s_{j,VT_Region5} - S_{VT_Region5})$	0.18	0.22	0.21
$Var(s_{j,VT_Region6} - S_{VT_Region6})$	0.12	0.13	0.27
$Var(s_{j,VT_Region7} - S_{VT_Region7})$	0.13	0.13	0.28
$Var(s_{j,VT_Region8} - S_{VT_Region8})$	0.11	0.11	0.20
Contribution within	0.52	0.50	0.75
Contribution within with controls	0.46	0.43	0.71

Note: Technology measures are weighted by the sampling weights. Contribution within with controls is estimated after controlling for size group small, medium and large), sector (agriculture, manufacturing and services), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status. Vietnam regions are as follows: Region 1 (Bac Ninh; Haiphong; Ninh Binh), Region 2 (Thai Nguyen; Bac Giang), Region 3 (Thanh Hoa; Ha Tinh; Binh Dinh), Region 4 (Kon Tum; Lam Dong), Region 5 (Binh Duong; Dong Nai), Region 6 (Long An; Vinh Long), Region 7 (Ha Noi), and Region 8 (Ho Chi Minh). Estimates are weighted by the sampling weights.

C.3 Detailed controls for sector effects

This section provides additional results that help us understand the role of sectoral composition in some of the results concerning cross-firm and cross-country differences in technology sophistication, as well as the covariation between technology sophistication and firm-level characteristics. All the exercises we conduct consists in redoing some of the analyses from the main text but trying to keep more constant the sectoral classification of the firms. By keeping constant the sector of analysis across countries, we can be sure that the robustness of the fact (relative to the baseline for the entire economy) demonstrates that it is not driven by differences in sectoral composition across countries. In the first two exercises we focus on each of the four subsectors for which the survey is stratified across countries. These are Agriculture-Crops, Food Processing, Wearing Apparel, and Wholesale and Retail. In the last exercise, we use a traditional decomposition of the entire economy in three sectors (agriculture, manufacturing and services). First, we explore whether cross-country differences in average technology sophistication presented in Table 2 are driven by cross-country differences in the sectoral composition. To demonstrate that this is not the case, Table C.4 examines the average technology sophistication (ABF, GBF, and SSBF) and the relative gap between Brazil and Senegal in each of the four sub-sectors. Interestingly, of these four subsectors, one belongs to agriculture, two to manufacturing and the fourth to services. The main observation is that all the findings in Table 2 (including the ranking of average sophistication by country, and the ranking of sophistication gaps (Brazil-Senegal) across sectors, hold for the narrower sectoral classifications. Hence, limiting the role for sectoral heterogeneity in driving the results. Second, we explore the role of sectoral heterogeneity in the relative magnitude of cross-firm variance and cross-country variance in sophistication by conducting the within-between decomposition in each of the four subsectors. (See Tables C.5, C.6, C.7 and C.8). Overall, the Tables support the magnitude of the within-country component, although it is smaller than in the full sample. In the last exercise, we re-compute Table 4 in each of the three broad sectors: Agriculture in Table C.9, Manufacturing in Table C.10, and Services in Table C.11. The results are very robust across sectors. In particular, the country dummies are all consistent, and we find a consistent coefficient of firm size, exporter and multinational status and a lack of association between technology sophistication and firm age, which are all in line with the baseline results in the text.

Table C.4: Average Technology Sophistication in Agriculture–Crops, Food Processing, Wearing Apparel, and Wholesale and Retail

	ABF	GBF	SSBF
Average sophistication			
Agriculture–Crops	1.85	1.67	2.10
Food Processing	1.77	1.75	1.77
Wearing Apparel	1.77	1.75	1.80
Wholesale and Retail	1.83	1.96	1.66
Gap: BR - SN			
Agriculture–Crops	30%	25%	37%
Food Processing	17%	20%	12%
Wearing Apparel	24%	26%	21%
Wholesale and Retail	26%	33%	17%

Note: Average sophistication reports the average of technology sophistication across countries (Brazil, Vietnam, and Senegal) conditional on each sub-sector (Agriculture–Crops, Food Processing, Wearing Apparel, and Wholesale and Retail). Gap shows the the difference in technology sophistication between Brazil and Senegal. Estimates are weighted by the sampling weights.

Table C.5: Cross-Firm Variance in Technology Sophistication in Agriculture

	ABF	GBF	SSBF
$Var(S_c - S)$	0.13	0.09	0.20
$Var(s_j - S_c)$	0.08	0.08	0.19
$Var(s_{j,Brazil} - S_{Brazil})$	0.28	0.53	0.25
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.13	0.17	0.19
$Var(s_{j,Senegal} - S_{Senegal})$	0.06	0.03	0.18
Contribution within	0.38	0.47	0.48
Contribution within with controls	0.28	0.39	0.39

Note: Contribution within with controls is estimated after controlling for size group small, medium and large), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status. Estimates are weighted by the sampling weights.

Table C.6: Cross-Firm Variance in Technology Sophistication in Food Processing

	ABF	GBF	SSBF
$Var(S_c - S)$	0.10	0.14	0.05
$Var(s_j - S_c)$	0.16	0.23	0.29
$Var(s_{j,Brazil} - S_{Brazil})$	0.27	0.44	0.43
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.14	0.22	0.32
$Var(s_{j,Senegal} - S_{Senegal})$	0.11	0.11	0.21
Contribution within	0.61	0.62	0.86
Contribution within with controls	0.46	0.47	0.76

Note: Contribution within with controls is estimated after controlling for size group small, medium and large), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status. Estimates are weighted by the sampling weights.

Table C.7: Cross-Firm Variance in Technology Sophistication in Wearing Apparel

	ABF	GBF	SSBF
$Var(S_c - S)$	0.15	0.27	0.07
$Var(s_j - S_c)$	0.18	0.26	0.24
$Var(s_{j,Brazil} - S_{Brazil})$	0.28	0.44	0.28
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.10	0.11	0.23
$Var(s_{j,Senegal} - S_{Senegal})$	0.11	0.13	0.19
Contribution within	0.55	0.48	0.78
Contribution within with controls	0.49	0.43	0.73

Note: Contribution within with controls is estimated after controlling for size group small, medium and large), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status. Estimates are weighted by the sampling weights.

Table C.8: Cross-Firm Variance in Technology Sophistication in Wholesale and Retail

	ABF	GBF	SSBF
$Var(S_c - S)$	0.16	0.19	0.13
$Var(s_j - S_c)$	0.06	0.10	0.12
$Var(s_{j,Brazil} - S_{Brazil})$	0.19	0.35	0.25
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.09	0.12	0.29
$Var(s_{j,Senegal} - S_{Senegal})$	0.02	0.02	0.07
Contribution within	0.27	0.34	0.49
Contribution within with controls	0.25	0.32	0.46

Note: Contribution within with controls is estimated after controlling for size group small, medium and large), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status. Estimates are weighted by the sampling weights.

Table C.9: Technology Sophistication and Firm Characteristics, Agriculture

VARIABLES	(1) ABF	(2) GBF	(3) SSBF
Vietnam	-0.48***	-0.50***	-0.50***
	(0.10)	(0.10)	(0.15)
Senegal	-1.13***	-1.07***	-1.24***
	(0.05)	(0.06)	(0.08)
Medium	0.12***	0.09*	0.16**
	(0.04)	(0.05)	(0.07)
Large	0.27***	0.25***	0.27***
	(0.07)	(0.07)	(0.10)
Age 6 to 10	0.27***	0.09	0.39***
	(0.08)	(0.08)	(0.12)
Age 11 to 15	0.09	0.05	0.18
	(0.08)	(0.08)	(0.11)
Age 16+	0.06	0.08	-0.01
	(0.06)	(0.07)	(0.09)
Foreign Owned	0.38*	0.46**	0.49
	(0.20)	(0.22)	(0.31)
Exporter	0.29***	0.41***	0.12
	(0.07)	(0.08)	(0.11)
Observations	351	351	347
R-squared	0.67	0.59	0.53

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

Table C.10: Technology Sophistication and Firm Characteristics, Manufacturing

VARIABLES	(1) ABF	(2) GBF	(3) SSBF
Vietnam	-0.30***	-0.30***	-0.33***
	(0.02)	(0.03)	(0.03)
Senegal	-0.77***	-0.82***	-0.64***
	(0.02)	(0.03)	(0.03)
Medium	0.18***	0.21***	0.07**
	(0.02)	(0.02)	(0.03)
Large	0.54***	0.60***	0.28***
	(0.04)	(0.04)	(0.05)
Age 6 to 10	0.01	0.03	0.00
	(0.03)	(0.03)	(0.04)
Age 11 to 15	0.01	0.03	0.01
	(0.03)	(0.03)	(0.04)
Age 16+	-0.01	0.01	-0.02
	(0.02)	(0.03)	(0.03)
Foreign Owned	0.22***	0.22***	0.22***
	(0.04)	(0.04)	(0.05)
Exporter	0.11***	0.10***	0.08**
	(0.02)	(0.02)	(0.03)
Observations	1,856	1,856	1,841
R-squared	0.60	0.58	0.29

Note: *** p < 0.01, ** p< 0.05, * p <0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

Table C.11: Technology Sophistication and Firm Characteristics, Services

VARIABLES	(1) ABF	(2) GBF	(3) SSBF
Vietnam	-0.43***	-0.62***	0.06
	(0.03)	(0.03)	(0.04)
Senegal	-1.01***	-1.19***	-0.62***
	(0.03)	(0.03)	(0.04)
Medium	0.23***	0.26***	0.12***
	(0.03)	(0.03)	(0.04)
Large	0.57***	0.63***	0.47***
	(0.05)	(0.06)	(0.09)
Age 6 to 10	-0.04	-0.05	-0.07
	(0.03)	(0.04)	(0.05)
Age 11 to 15	-0.03	-0.04	-0.02
	(0.03)	(0.04)	(0.05)
Age 16+	0.03	0.04	0.07
	(0.03)	(0.03)	(0.05)
Foreign Owned	0.28***	0.29***	0.30***
	(0.05)	(0.05)	(0.09)
Exporter	0.14***	0.12***	0.11**
	(0.04)	(0.04)	(0.05)
Observations	1,689	1,689	888
R-squared	0.49	0.53	0.26

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

D Mathematical derivations for Section 5 and 6, and estimation strategy for the technology curve

In this section we formally derive some of the key theoretical results in sections 5 and 6, and explain in detail the estimation of the structural parameters of the technology curve in equation (10).

Relationship between a_j and s_j Consider the non-homothetic CES aggregator which implicitly defines the technology index a_j:

$$\sum_{f=1}^{N_f} \left(\Omega_f^{\frac{1}{\sigma}} e^{\frac{\varepsilon_f a_j}{\sigma}}\right) e^{\frac{\sigma-1}{\sigma} s_{f,j}} = 1 \tag{D.1}$$

As discussed in Comin, Lashkari and Mestieri (2021), we can normalize the value of the shifter Ω_f, and the elasticity ε_f for an arbitrary business function[86] to arbitrary positive values without any implication on the technology choices made by firms. Below we use this property to normalize the value of the elasticity $\varepsilon_{\overline{f}}$ in a base business function $\overline{f}$.

Next, we explore in more detail the properties of the technology index implicitly defined by (D.1). To this end, we first define a as

$$\sum_{f=1}^{N_f} \left(\Omega_f^{\frac{1}{\sigma}} e^{\frac{\varepsilon_f a}{\sigma}}\right) e^{\frac{\sigma-1}{\sigma} s} = 1 \tag{D.2}$$

where $s = \frac{\sum_{j=1}^{N_j} s_j}{N_j}$ is the average sophistication across firms. In words, a is the level of the technology index implicitly defined by (1) in a firm that has sophistication level s in all its business functions.

To explore the relationship between a_j and s_j, we conduct a log-linearization of (D.1) around (s,a). The approximation yields:

$$0 \simeq \sum_{f=1}^{N_f} \omega_f \left[\left[\frac{\varepsilon_f}{\sigma}(a_j - a)\right] + \frac{\sigma-1}{\sigma}(s_{f,j} - s)\right] \tag{D.3}$$

where

$$\omega_f = \left(\xi_f^{\frac{1}{\sigma}} e^{\frac{\varepsilon_f a}{\sigma}}\right) e^{\frac{\sigma-1}{\sigma} s} \tag{D.4}$$

Note that $\omega_f > 0$, and from (D.2), $\sum_{f=1}^{N_f} \omega_f = 1$. Let's define $\overline{\varepsilon} = \sum_{f=1}^{N_f} \omega_f \varepsilon_f$. Equation

[86] Not necessarily the same for both.

(D.3) implies that

$$
\begin{aligned}
a_j &\simeq a + \frac{(1-\sigma)}{\overline{\varepsilon}} \sum_{f=1}^{N_f} \omega_f (s_{f,j} - s) \\
&= a + \frac{(1-\sigma)}{\overline{\varepsilon}} \left[\left(\sum_{f=1}^{N_f} (\omega_f - \frac{1}{N_f}) s_{f,j} \right) + s_j - s \right] \\
&= a + \frac{(1-\sigma)}{\overline{\varepsilon}} \left[s_j - s + Cov(\omega_f, s_{f,j}) \right] \\
&= a - \frac{(1-\sigma)}{\overline{\varepsilon}} s + \frac{(1-\sigma)}{\overline{\varepsilon}} s_j + \frac{(1-\sigma)}{\overline{\varepsilon}} \sqrt{WVar_j * Var(\omega_f)} * Corr(\omega_f, s_{f,j}) \qquad \text{(D.5)}
\end{aligned}
$$

Expression (D.5) shows that a_j is approximately equal to the sum of three terms. The first is a constant ($a - \frac{(1-\sigma)}{\overline{\varepsilon}} s$). The second is proportional to s_j. The third term captures the covariance between the weight of function f, ω_f, and the sophistication level in function f in firm j, $s_{f,j}$. If the sophistication level of all functions was the same (i.e., $WVar_j = 0$), all functions had the same weight (i.e., $\omega_f = 1/N_f$) or if the sophistication and weights of business functions were uncorrelated, then the technology index, to a first order, would be a linear function of the average sophistication level s_j. However, the possibility that firms have greater sophistication in functions that are more important introduces a positive wedge between the technology index and the average sophistication level. If the correlation between these two variables is positive, the wedge is increasing in the within firm variance ($WVar_j$). Note additionally, the connection between equations (D.5 and 10). In particular, the parameter ϱ in equation (10) is equal to $\sqrt{Var(\omega_f)} * Corr(\omega_f, s_{f,j})$.

Optimal sophistication levels Consider the optimization problem presented in section 5.2. Firm j selects the sophistication level for each business function to maximize the operating profits, $\Pi(a_j)$, net of the cost of implementing the technologies, $\sum_{f=1}^{N_f} (C_j C_{f,X} e^{s_{f,j}})$, subject to the constraint (D.1).

$C_{f,X}$ is a parameter that depends on the business function as well as firm characteristics (X). We assume that $\Pi_j(a_j)$ is concave in a_j. The first order conditions for this problem are

$$
\Pi_j'(a_j) \frac{\frac{(1-\sigma)}{\sigma} \left(\Omega_f^{\frac{1}{\sigma}} e^{\frac{\varepsilon_f a_j}{\sigma}} \right) e^{\frac{\sigma-1}{\sigma} s_{f,j}}}{\sum_{f=1}^{N_f} \frac{\varepsilon_f}{\sigma} \left(\Omega_f^{\frac{1}{\sigma}} e^{\frac{\varepsilon_f a_j}{\sigma}} \right) e^{\frac{\sigma-1}{\sigma} s_{f,j}}} = C_j C_{f,X} e^{s_{f,j}} \qquad \text{(D.6)}
$$

Taking logs and isolating $s_{f,j}$, we obtain

$$s_{f,j} = \overbrace{\sigma ln(\frac{(1-\sigma)}{\sigma}) + ln(\Omega_f)}^{\kappa_f} - \sigma ln(C_{f,X})$$

$$+ \overbrace{\sigma ln(\Pi'_j(a_j)) - \sigma ln(C_j) - \sigma ln(\sum_{f=1}^{N_f} \frac{\varepsilon_f}{\sigma} \left(\Omega_f^{\frac{1}{\sigma}} e^{\frac{\varepsilon_f a_j}{\sigma}}\right) e^{\frac{\sigma-1}{\sigma} s_{f,j}})}^{\kappa_j} + \varepsilon_f a_j \quad \text{(D.7)}$$

which is the expression in specification (8).

Estimation of the technology curve

To estimate the technology curve (D.8) we proceed as follows.

$$s_{f,j} = \alpha_j + \alpha_f + \varepsilon_f^{\beta} \left(s_j + \varrho * \sqrt{WVar_j}\right) + \upsilon_{f,j} \quad \text{(D.8)}$$

First, we differentiate (D.8) with respect to a base business function, $\overline{f}$, (which we make business administration, as this is a function available for all firm) and obtain:

$$s_{f,j} - s_{\overline{f},j} = \alpha_f - \alpha_{\overline{f}} + \left(\varepsilon_f^{\beta} - \varepsilon_{\overline{f}}^{\beta}\right) \left(s_j + \varrho * \sqrt{WVar_j}\right) + \left(\upsilon_{f,j} - \upsilon_{\overline{f},j}\right)$$
$$\widehat{s}_{f,j} = \widehat{\alpha}_f + \widehat{\varepsilon}_f^{\beta} \left(s_j + \varrho * \sqrt{WVar_j}\right) + \widehat{\upsilon}_{f,j} \quad \text{(D.9)}$$

where $\widehat{x}_{f,j} = x_{f,j} - x_{\overline{f},j}$ for a generic variable x. Note that the the firm fixed effect, α_j, has dropped from (D.9).

Then, we estimate:

$$\widehat{s}_{f,j} = \widehat{\alpha}_f + \widehat{\varepsilon}_f^{\beta} * s_j + \widehat{\varepsilon}_f^{\varrho} * \sqrt{WVar_j} + \widehat{\upsilon}_{f,j} \quad \text{(D.10)}$$

using non-linear least squares imposing the constraint $\widehat{\varepsilon}_f^{\varrho} = \varrho \widehat{\varepsilon}_f^{\beta}$ for all functions f, where ϱ is constant across business functions.

The within-firm R^2 (reported in Tables 7, 8, E.5, E.6, and E.7) are computed as

$$R_C^2 = \frac{Cov(\widehat{s}_{f,j}, \widehat{s}_{f,j}^p)}{Var(\widehat{s}_{f,j})}, \quad \text{(D.11)}$$

where $\widehat{s}_{f,j} = s_{f,j} - s_{\overline{f},j}$, $\widehat{s}_{f,j}^p$ is the predicted $\widehat{s}_{f,j}$ from equation (D.10) and the covariance and variance are computed for all firms and business functions of the relevant broad class of business functions. Table 7 reports the fit of the technology curves for the GBFs and the four SSBFs for which we have the largest number of establishments. The within-R^2 for all the business functions is 0.32.

In the presence of firm-level fixed effects α_j, we cannot identify $\varepsilon^{\beta}_{\overline{f}}$. As discussed above, this has no relevance for the firm choices as the aggregator (D.1) permits an arbitrary normalization of $\varepsilon_{\overline{f}}$. This normalization has a one-to-one mapping with the level of $\varepsilon^{\beta}_{\overline{f}}$. Accordingly, we normalize $\varepsilon^{\beta}_{\overline{f}}$ by implementing the econometric analog to matching the slope of the technology curve for business administration plotted in Figures 8a and 9a. Formally, we define $y_{f,j} = s_{f,j} - \widehat{\varepsilon}^{\beta}_{f}(s_j + \varrho * \sqrt{WVar_j})$, where $\widehat{\varepsilon}_f$ and ϱ are the estimates from equation (D.10). Then we estimate

$$y_{f,j} = \alpha_f + \varepsilon^{\beta}_{\overline{f}} * \left(s_j + \varrho * \sqrt{WVar_j}\right) + w_{f,j} \tag{D.12}$$

where $\varepsilon^{\beta}_{\overline{f}}$ is constant across business functions, and where we have omitted the firm-level fixed effects α_j. We stress that this normalization has no bearing for the cross-function dispersion in the slope of technology curves or for the share of within-firm variance in technology sophistication accounted by technology curves (i.e., the within-R^2).

Sophistication and productivity In section 6.1 we discuss the channels that connect firm productivity and the technology index a_j. The first channel is the markup while the second one is the elasticity of output with respect to labor ($\frac{\partial \epsilon_{F,L}}{\partial a_j}$). Next, we present two production functions that satisfy the condition that the elasticity is decreasing with a_j.

$$F_j = e^{a_j} L_j^{\alpha(a_j)} \tag{D.13}$$

where $\alpha'(a_j) < 0$.

$$F_j = e^{a_j} L_j^{\alpha} - \kappa \tag{D.14}$$

where κ is an overhead cost.

Reduced form for firm-level productivity In equation (13) we introduce a reduced form to explore econometrically the relationship between firm productivity and the sophistication measures (s_j and $Wvar_j$). Next we derive the reduced form from equations (12) and (7).

Approximating $ln(VAPW_j)$ around the sample average, $\overline{ln(VAPW)}$, we obtain

$$\begin{aligned} ln(VAPW_j) &= \overline{ln(VAPW)} + \kappa * (a_j - \overline{a}) \\ &= \overline{ln(VAPW)} + \kappa * (\beta * (s_j - \overline{s}) + \gamma * (\sqrt{WVar_j} - \overline{\sqrt{WVar}})) \end{aligned} \tag{D.15}$$

where κ is the right hand side of (12) evaluated at the sample average, and the second row of (D.15) uses (7) to substitute in for $(a_j - \overline{a})$. Note that this specification assumes that $gamma_j$ is constant across firms. The specification in column 5 of Table 9 introduces an interaction between the within-firm dispersion in sophistication and s_j which generalizes equation (D.15) to the case where γ varies across firms.

E Results referred to in Section 5

This section contains additional results concerning within-firm variance in technology sophistication and reports the estimates of the technology curve. First, we show that the estimates of specification (5) for the within-firm variance in technology sophistication are robust to including other controls, (i) replacing the categorical dummies for age and size by continuous variables (Table E.1) and (ii) including controls for the number of business functions (Table E.2) and log number of business functions (Table E.3). Table E.4 reports the average within-firm variance of technology sophistication by country and sector. Tables E.5 and E.6 reports the slopes of the technology curves for business functions not reported in Table 8 in the main text. We reports the estimates of technology curves for the GBFs and the four main SSBFs proxying log $ln(C_{f,x})$ by log firm employment interacted with a full set of business function dummies. (See equation (8).)

Table E.1: Within-Firm Variance in Technology Sophistication and Firm Characteristics, Robustness

VARIABLES	(1) Var(ABF)	(2) Var(GBF)	(3) Var(SSBF)
s_j	1.50***	1.55***	1.38***
	(0.07)	(0.08)	(0.14)
s_j^2	-0.26***	-0.29***	-0.20***
	(0.02)	(0.02)	(0.03)
Vietnam	-0.35***	-0.47***	0.02
	(0.02)	(0.02)	(0.03)
Senegal	-0.17***	-0.31***	0.26***
	(0.02)	(0.03)	(0.04)
Manuf	0.03	0.13***	-0.02
	(0.04)	(0.04)	(0.05)
SVC	0.04	0.16***	-0.12**
	(0.03)	(0.04)	(0.05)
Size	0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)
Age	0.00	0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
Foreign owned	0.03	0.06*	0.05
	(0.03)	(0.03)	(0.06)
Exporter	0.04*	0.01	0.04
	(0.02)	(0.02)	(0.03)
Observations	3,884	3,879	2,258
R-squared	0.43	0.42	0.21

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Estimates are weighted by the sampling weights. Robust standard errors in parenthesis.

Table E.2: Within-Firm Variance in Technology Sophistication and Firm Characteristics, Robustness

VARIABLES	(1) Var(ABF)	(2) Var(GBF)	(3) Var(SSBF)
s_j	1.53***	1.55***	1.40***
	(0.07)	(0.08)	(0.14)
s_j^2	-0.27***	-0.29***	-0.21***
	(0.02)	(0.02)	(0.03)
Vietnam	-0.36***	-0.49***	0.05
	(0.02)	(0.02)	(0.03)
Senegal	-0.18***	-0.32***	0.26***
	(0.02)	(0.03)	(0.04)
Manuf	0.01	0.11***	-0.01
	(0.04)	(0.04)	(0.05)
SVC	0.01	0.14***	-0.10**
	(0.04)	(0.04)	(0.05)
Medium	-0.02	-0.01	0.02
	(0.02)	(0.02)	(0.03)
Large	0.04	0.05	-0.00
	(0.03)	(0.03)	(0.06)
Age 6 to 10	0.04**	0.03	0.07**
	(0.02)	(0.02)	(0.03)
Age 11 to 15	-0.01	-0.03	0.03
	(0.02)	(0.02)	(0.04)
Age 16+	0.02	0.01	0.07**
	(0.02)	(0.02)	(0.03)
Foreign owned	0.02	0.06*	0.05
	(0.03)	(0.03)	(0.06)
Exporter	0.05***	0.02	0.04
	(0.02)	(0.02)	(0.03)
N of Business Functions	-0.01***	-0.00	0.01
	(0.00)	(0.00)	(0.01)
Observations	3,893	3,888	2,267
R-squared	0.43	0.42	0.21

Note: *** p < 0.01, ** p< 0.05, * p <0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Estimates are weighted by the sampling weights. Robust standard errors in parentheses.

Table E.3: Within-Firm Variance in Technology Sophistication and Firm Characteristics, Robustness

VARIABLES	(1) Var(ABF)	(2) Var(GBF)	(3) Var(SSBF)
s_j	1.53***	1.54***	1.40***
	(0.07)	(0.08)	(0.14)
s_j^2	-0.27***	-0.28***	-0.21***
	(0.02)	(0.02)	(0.03)
Vietnam	-0.36***	-0.49***	0.05*
	(0.02)	(0.02)	(0.03)
Senegal	-0.19***	-0.32***	0.26***
	(0.02)	(0.03)	(0.04)
Manuf	0.01	0.12***	-0.01
	(0.04)	(0.04)	(0.05)
SVC	0.01	0.15***	-0.10**
	(0.04)	(0.04)	(0.05)
Medium	-0.02	-0.01	0.02
	(0.02)	(0.02)	(0.03)
Large	0.04	0.05	-0.00
	(0.03)	(0.03)	(0.06)
Age 6 to 10	0.04**	0.03	0.07**
	(0.02)	(0.02)	(0.03)
Age 11 to 15	-0.01	-0.03	0.03
	(0.02)	(0.02)	(0.04)
Age 16+	0.02	0.01	0.07**
	(0.02)	(0.02)	(0.03)
Foreign owned	0.02	0.06*	0.05
	(0.03)	(0.03)	(0.06)
Exporter	0.05**	0.02	0.04
	(0.02)	(0.02)	(0.03)
Ln(N of Business Functions)	-0.08***	-0.02	0.04
	(0.02)	(0.03)	(0.08)
Observations	3,893	3,888	2,267
R-squared	0.43	0.42	0.21

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Robust standard errors in parentheses.

Table E.4: Average Within-Firm Variance of Technology Sophistication by Country and Sector

	ABF			GBF			SSBF		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	0.54	0.54	0.58	0.48	0.56	0.62	0.54	0.21	0.27
Brazil (BR)	1.01	1.02	0.90	1.03	1.09	1.01	0.83	0.37	0.39
Vietnam (VT)	0.42	0.40	0.50	0.34	0.42	0.50	0.50	0.09	0.27
Senegal (SN)	0.19	0.20	0.34	0.08	0.17	0.35	0.30	0.17	0.15
Gap: BR - SN	0.82	0.82	0.56	0.95	0.92	0.66	0.53	0.20	0.24
Relative Gap**	21%	21%	14%	24%	23%	17%	13%	5%	6%

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

Table E.5: Technology Curve for Livestock, Automotive, Pharmaceutical, and Leather and Footwear

Livestock		Automotive		Pharmaceutical		Leather and Footwear	
$\epsilon^{\beta}_{Breeding}$	1.69***	$\epsilon^{\beta}_{Assembly}$	2.42	$\epsilon^{\beta}_{Facilities}$	2.15	$\epsilon^{\beta}_{Design}$	2.55***
	(0.41)		(2.61)		(1.88)		(0.97)
$\epsilon^{\beta}_{Nutrition}$	0.70**	$\epsilon^{\beta}_{Pressing}$	0.36	$\epsilon^{\beta}_{Weighing}$	1.3	$\epsilon^{\beta}_{Cutting}$	1.53*
	(0.35)		(1.25)		(1.60)		(0.79)
$\epsilon^{\beta}_{AnimalHealth}$	0.62*	$\epsilon^{\beta}_{Painting}$	-0.12	$\epsilon^{\beta}_{Compounding}$	1.43	$\epsilon^{\beta}_{Sewing}$	1.34
	(0.33)		(1.36)		(1.62)		(0.86)
$\epsilon^{\beta}_{Monitoring}$	0.62*	$\epsilon^{\beta}_{Molding}$	2.14	$\epsilon^{\beta}_{Encapsulation}$	1.2	$\epsilon^{\beta}_{Finishing}$	1.11
	(0.32)		(3.85)		(2.60)		(0.83)
$\epsilon^{\beta}_{AnimalTransp}$	0.48	$\epsilon^{\beta}_{Management}$	1.39	$\epsilon^{\beta}_{Quality}$	2.68	$\epsilon^{\beta}_{Fabrication}$	0.92
	(0.39)		(1.27)		(1.74)		(0.75)
		$\epsilon^{\beta}_{Fabrication}$	-0.01	$\epsilon^{\beta}_{Packaging}$	2.31		
			(0.66)		(1.75)		
				$\epsilon^{\beta}_{Fabrication}$	1.00		
					(1.60)		

Note: *** p<0.01, ** p<0.05, * p<0.1. Business function-level technology sophistication is regressed on firm-level technology sophistication with controlling for firm-size interacted with each business function, using nonlinear least-squares estimation. The parameter ϵ^{β}_{f} for general business functions and ϱ are reported in this table. Estimates are weighted by the sampling weights. Standard errors in parentheses.

Table E.6: Technology Curve for Finance, Transportation, Health Services, and Other Manufacturing

Finance		Transportation		Health Services		Other Manufacturing	
$\epsilon^{\beta}_{CustomerServ}$	-0.51	$\epsilon^{\beta}_{Planning}$	1.54***	$\epsilon^{\beta}_{Machines}$	1.62***	$\epsilon^{\beta}_{Fabrication}$	0.59***
	(0.76)		(0.50)		(0.42)		(0.07)
$\epsilon^{\beta}_{Verification}$	-0.05	$\epsilon^{\beta}_{Execution}$	1.64***	$\epsilon^{\beta}_{Scheduling}$	0.78*		
	(0.87)		(0.52)		(0.40)		
$\epsilon^{\beta}_{LoanApplic}$	0.93	$\epsilon^{\beta}_{Monitoring}$	1.33***	$\epsilon^{\beta}_{Records}$	1.67***		
	(0.73)		(0.51)		(0.38)		
$\epsilon^{\beta}_{LoanApprov}$	-0.45	$\epsilon^{\beta}_{Performance}$	1.50***	$\epsilon^{\beta}_{Procedures}$	1.66***		
	(0.81)		(0.47)		(0.49)		
$\epsilon^{\beta}_{SupportArea}$	0.86	$\epsilon^{\beta}_{Maintenance}$	1.09*				
	(0.83)		(0.56)				

Note: *** p<0.01, ** p<0.05, * p<0.1. Business function-level technology sophistication is regressed on firm-level technology sophistication with controlling for firm-size interacted with each business function, using nonlinear least-squares estimation. The parameter ϵ^{β}_{f} for general business functions and ϱ are reported in this table. Estimates are weighted by the sampling weights. Standard errors in parentheses.

Table E.7: Technology Curve Allowing for Function-Specific Firm Size Effects

General Business		Agriculture - Crops		Food Processing		Wearing Apparel		Wholesale & Retail	
ϵ^{β}_{Admin}	1.80***	$\epsilon^{\beta}_{Irrigation}$	2.08***	$\epsilon^{\beta}_{FoodStorage}$	1.22***	$\epsilon^{\beta}_{Design}$	0.96***	$\epsilon^{\beta}_{Advert}$	0.80***
	(0.01)		(0.26)		(0.23)		(0.20)		(0.09)
$\epsilon^{\beta}_{Planning}$	1.58***	$\epsilon^{\beta}_{LandPrep}$	1.54***	$\epsilon^{\beta}_{Packaging}$	0.96***	$\epsilon^{\beta}_{Finishing}$	0.86***	$\epsilon^{\beta}_{Inventory}$	0.73***
	(0.03)		(0.24)		(0.22)		(0.20)		(0.06)
$\epsilon^{\beta}_{Sourcing}$	1.26***	$\epsilon^{\beta}_{Storage}$	1.50***	$\epsilon^{\beta}_{AntiBact}$	0.82***	$\epsilon^{\beta}_{Cutting}$	0.71***	$\epsilon^{\beta}_{Pricing}$	0.65***
	(0.03)		(0.26)		(0.25)		(0.19)		(0.06)
$\epsilon^{\beta}_{Marketing}$	0.67***	$\epsilon^{\beta}_{Harvest}$	1.26***	$\epsilon^{\beta}_{InputTest}$	0.70***	$\epsilon^{\beta}_{Sewing}$	0.47**	$\epsilon^{\beta}_{Merchand}$	0.39***
	(0.03)		(0.26)		(0.26)		(0.21)		(0.06)
$\epsilon^{\beta}_{Quality}$	0.61***	$\epsilon^{\beta}_{PestControl}$	1.14***	$\epsilon^{\beta}_{Blending}$	0.58***	$\epsilon^{\beta}_{Fabrication}$	0.27	$\epsilon^{\beta}_{CustomServ}$	0.08
	(0.05)		(0.27)		(0.22)		(0.18)		(0.07)
$\epsilon^{\beta}_{Payment}$	0.55***	$\epsilon^{\beta}_{Packaging}$	0.31	$\epsilon^{\beta}_{Fabrication}$	0.39*				
	(0.03)		(0.30)		(0.20)				
ϵ^{β}_{Sale}	0.21***								
	(0.03)								
ϱ	0.17***								
	(0.02)								
Within-firm R^2	0.35								

Note: *** p<0.01, ** p<0.05, * p<0.1. Business function-level technology sophistication is regressed on firm-level technology sophistication with controlling for firm-size interacted with each business function, using nonlinear least-squares estimation. The parameter ϵ^{β}_{f} for general business functions and ϱ are reported in this table. Estimates are weighted by the sampling weights. Standard errors in parentheses.

F Results referred to in Section 6

In this section we extend the analysis of the relationship between technology sophistication and firm productivity by controlling for firm-level capital to labor ratio and the quality of workers. We first use data on the firms' book value of capital to measure capital per employee and run the following regression:

$$ln(VAPW)_{j,c} = \alpha_c + \beta_s + \gamma T_{j,c} + \rho X_{j,c} + \theta ln(K/L)_{j,c} + v_{j,c} \quad \text{(F.1)}$$

where $ln(VAPW)_{j,c}$ is the value added per worker and $ln(K/L)_{j,c}$ is the capital per worker. The results are provided in Tables F.8 and F.9.

We also estimate the productivity regression controlling for both capital per worker and labor cost per worker (our proxy for the average human capital of workers in the firm). The regression is specified as:

$$ln(VAPW)_{j,c} = \alpha_c + \beta_s + \gamma T_{j,c} + \rho X_{j,c} + \theta ln(K/L)_{j,c} + \lambda ln(LC/L)_{j,c} + v_{j,c} \quad \text{(F.2)}$$

where $ln(LC/L)_{j,c}$ is the labor cost per worker. The regression results are presented in Tables F.10 and F.11. The main findings found on the paper of a positive coefficient of technology sophistication on labor productivity remain robust.

Table F.8: Productivity and Technology Sophistication Controlling for ln(K/L)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
Ln(K/L)	0.28***	0.27***	0.27***	0.27***	0.27***	0.27***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
s_j	0.56***	2.43***	0.44***		1.94***	1.80***
	(0.10)	(0.50)	(0.11)		(0.58)	(0.61)
s_j^2		-0.43***			-0.34***	-0.19
		(0.10)			(0.12)	(0.15)
SD_j			0.63***		0.50***	1.71***
			(0.16)		(0.17)	(0.52)
a_j				0.57***		
				(0.09)		
$s_j \times SD_j$						-0.60***
						(0.22)
Firm Characteristics	√	√	√	√	√	√
Observations	2,519	2,519	2,519	2,519	2,519	2,519
R-squared	0.54	0.54	0.54	0.54	0.55	0.55

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table F.9: Productivity and Technology Sophistication Controlling for ln(K/L), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
Ln(K/L)	0.27***	0.27***	0.27***
	(0.04)	(0.04)	(0.04)
s_j^{GBF}	0.40***	0.41***	
	(0.10)	(0.10)	
s_j^{GBF}*Agriculture			0.29
			(0.29)
s_j^{GBF}*Manufacturing			0.58***
			(0.10)
s_j^{GBF}*Services			0.36***
			(0.12)
s_j^{SSBF}*Agriculture	0.24		
	(0.25)		
s_j^{SSBF}*Manufacturing	0.23***		
	(0.08)		
s_j^{SSBF}*Services	-0.09		
	(0.14)		
s_j^{SSBF}*Agriculture		0.25	0.32
		(0.25)	(0.27)
s_j^{SSBF}*Food Processing		0.31*	0.24
		(0.19)	(0.18)
s_j^{SSBF}*Apparel		0.51***	0.42***
		(0.15)	(0.15)
s_j^{SSBF}*Retail and Wholesale		-0.11	-0.07
		(0.15)	(0.15)
s_j^{SSBF}*Other Manufacturing		0.14*	0.08
		(0.08)	(0.08)
SD_j	0.63***	0.63***	0.60***
	(0.16)	(0.16)	(0.16)
Firm Characteristics	√	√	√
Observations	2,519	2,519	2,519
R-squared	0.54	0.54	0.55

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table F.10: Productivity and Technology Sophistication Controlling for ln(K/L) and ln(Labor Cost/L)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
Ln(K/L)	0.15***	0.14***	0.14***	0.14***	0.14***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Ln(Labor Cost/L)	0.70***	0.69***	0.69***	0.69***	0.69***	0.68***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
s_j	0.27***	1.65***	0.17		1.23**	1.15*
	(0.10)	(0.50)	(0.11)		(0.57)	(0.60)
s_j^2		-0.31***			-0.24**	-0.15
		(0.10)			(0.11)	(0.14)
SD_j			0.52***		0.43***	1.18**
			(0.14)		(0.16)	(0.50)
a_j				0.29***		
				(0.09)		
$s_j \times SD_j$						-0.38*
						(0.21)
Firm Characteristics	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Observations	2,496	2,496	2,496	2,496	2,496	2,496
R-squared	0.64	0.64	0.64	0.64	0.64	0.64

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table F.11: Productivity and Technology Sophistication Controlling for ln(K/L) and ln(Labor Cost/L), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
Ln(K/L)	0.14***	0.14***	0.14***
	(0.04)	(0.04)	(0.04)
Ln(Labor Cost/L)	0.69***	0.69***	0.69***
	(0.03)	(0.03)	(0.03)
s_j^{GBF}	0.12	0.13	
	(0.09)	(0.09)	
s_j^{GBF}*Agriculture			-0.11
			(0.22)
s_j^{GBF}*Manufacturing			0.25***
			(0.09)
s_j^{GBF}*Services			0.10
			(0.11)
s_j^{SSBF}*Agriculture	-0.15		
	(0.21)		
s_j^{SSBF}*Manufacturing	0.16**		
	(0.08)		
s_j^{SSBF}*Services	0.06		
	(0.14)		
s_j^{SSBF}*Agriculture		-0.15	-0.03
		(0.21)	(0.23)
s_j^{SSBF}*Food Processing		0.36**	0.31*
		(0.17)	(0.17)
s_j^{SSBF}*Apparel		0.26**	0.20
		(0.12)	(0.13)
s_j^{SSBF}*Retail and Wholesale		0.06	0.08
		(0.15)	(0.15)
s_j^{SSBF}*Other Manufacturing		0.09	0.04
		(0.08)	(0.08)
SD_j	0.51***	0.50***	0.49***
	(0.14)	(0.14)	(0.14)
Firm Characteristics	√	√	√
Observations	2,496	2,496	2,496
R-squared	0.64	0.64	0.64

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

G Robustness for cardinalization, sector disaggregation, and formality

This section contains robustness checks that cut across various sections in the paper. First, we explore the robustness of the results to using alternative cardinalizations of technology sophistication rankings constructed using different values of ϕ in expression (2). Second, we explore the robustness of the cross-firm analyses to including 4-digit SIC dummies in the analysis to control for sectoral heterogeneity within our broader sectoral aggregates. Finally, we show the robustness of our findings to restricting the data for Senegal to the subsample of firms that are classified as formal, despite the fact that the requirements for such a classification in Senegal are more stringent than in Vietnam and in Brazil.[87]

G.1 Alternative cardinalization parameters for sophistication rankings

A critical robustness test for our analysis is whether the results hold when using different cardinal transformations of our ordinal measures of technology sophistication. In this section, we re-estimate all the specifications in the main text for a wide range of ϕ (e.g., 1/3, 1/2, 2/3, 1.5, 2, 3) and find that the main results are robust to the value of the parameter ϕ used in equation (2)to cardinalize the sophistication rankings.

Table G.1 presents the robustness of pairwise correlation between technology sophistication and firm characteristics. The results show similar levels of positive correlations with firm characteristics across different ϕ.

In Table G.2 we investigate the robustness of the average technology sophistication by country using different ϕ. The magnitudes of the average sophistication and relative gaps decrease as ϕ increases, but the general rankings and patterns do not change. We also examine the robustness of the cross-country average technology sophistication by sector for ABF in Table G.3, GBF in Table G.4, and SSBF in Table G.5, with similar findings.

Table G.6 shows the results on the cross-firm variance in technology sophistication for different ϕ. In general, as ϕ increases, the cross-firm variance decreases but the within-country contribution increases. The table shows the consistency of the finding that the within-country component accounts for a significant share of the cross-firm variance in firm-level technology sophistication.

In Table G.7, we report the estimates of regressing s_j^{ϕ} on observable firm characteristics, for various values of ϕ. Although the magnitudes of the coefficients vary, the patterns do

[87] And that the prevalence of informality is greater in Senegal.

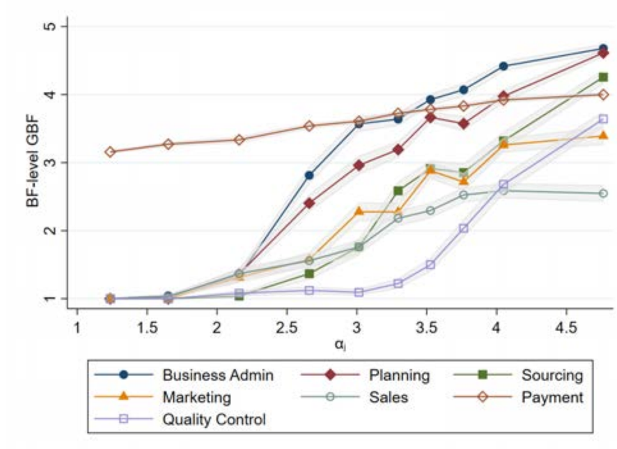
not change.

Table G.8 reports the within-firm variance in technology sophistication for different values of ϕ. The within-variance decreases as ϕ increases, but we firm that within-firm variance is approximately three times larger than cross-firm variance for all the values of ϕ. In Table G.9, we regress within-firm variance on technology sophistication and observable firm characteristics. As ϕ rises, the point estimate of technology sophistication declines without affecting much its significance All the specifications show quadratic relationship between within-firm variance and technology sophistication, except for $\phi = 3$. In general, we continue to find no clear pattern of association, for any given value of ϕ, between within-firm variance and firm age, size and multinational status. The positive association between within-firm variance and exporter status is robust. The R-squared of the regression tends to increase with ϕ.

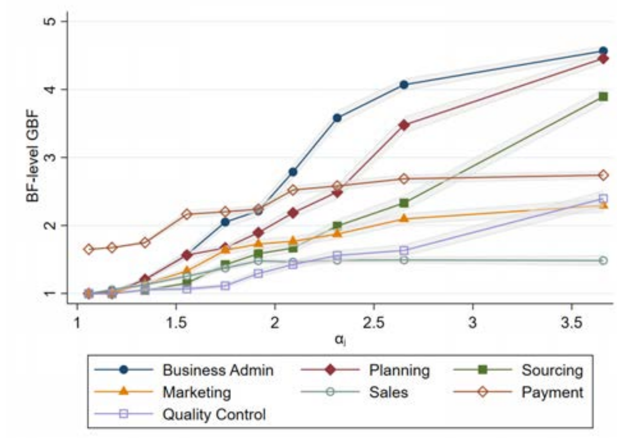
Then, we examine the robustness of the technology curves to the value of ϕ used in the cardinalization of technology sophistication. We constrcut firm-level technology indices using teh firm order aprpoximation in equation (7). As in Figure 8, we collapse firms into deciles of the distributions of a firm-level technology index, a_j^{ϕ} and plot for the average technology sophistication at the business function of the firms in each decile of the distribution of a_j, The technology curves for each general business function and SSBF (in the four largest sectors) across three values of ϕ (e.g., 1/3, 1, and 3) are provided in Figures G.1, G.2, G.3, G.4, and G.5. In the majority of the cases, we see that the shape of the technology curves and ranking of business functions by the slope of the technology curve is quite similar across ϕ's.

Finally, we re-estimate the productivity regressions using measures of technology sophistication constructed using different values of ϕ. The results for sophistication measures constructed using ABF are provided in Tables G.10, G.11, G.12, G.13, G.14, and G.15. The results where we allow for different coefficients for sophistication in GBF and SSBF are provided in Tables G.16, G.17, G.18, G.19, G.20, and G.21.

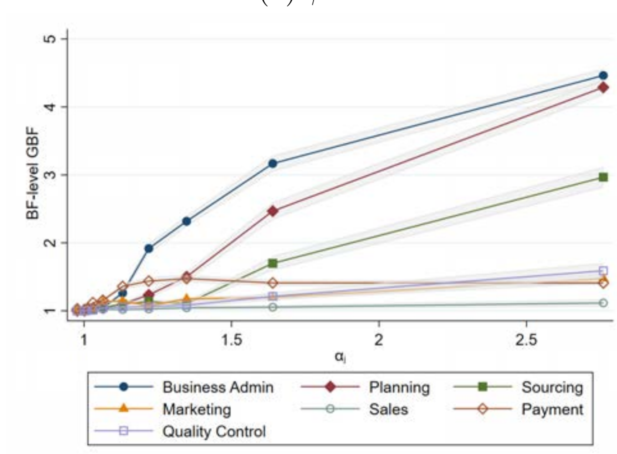
Overall, the results suggest that our findings are robust to cardinalizations of the sophistication rankings constructed with alternative values of ϕ.



(a) $\phi = 1/3$

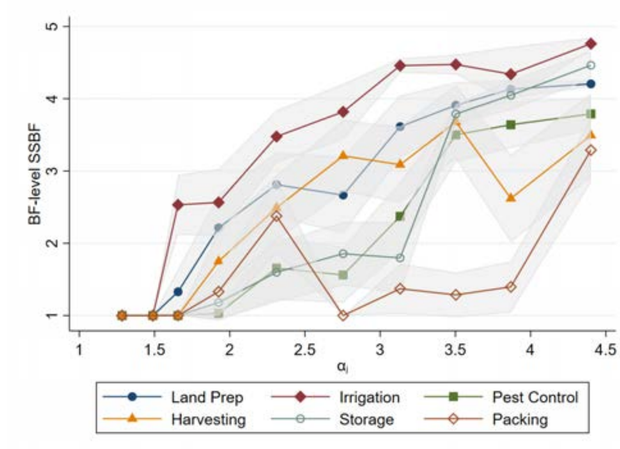


(b) $\phi = 1$

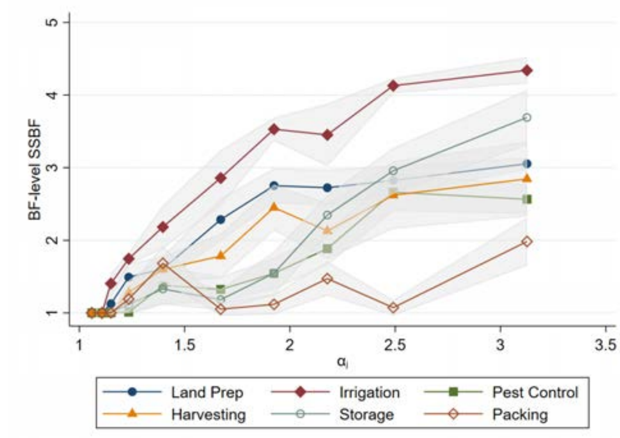


(c) $\phi = 3$

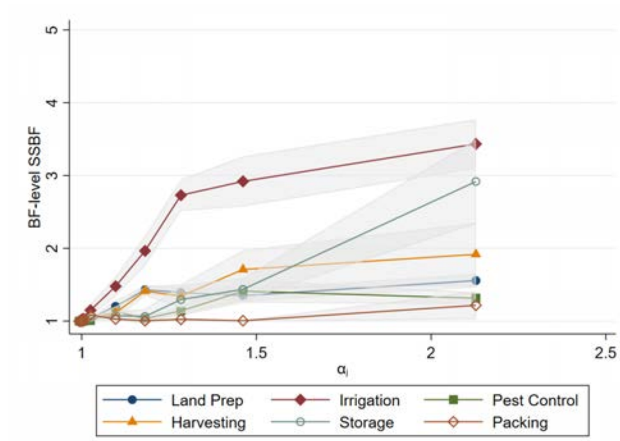
Figure G.1: Robustness of The Technology Curve, $s_{f,j}$ vs. α_j by Deciles, General Business Function



(a) $\phi = 1/3$

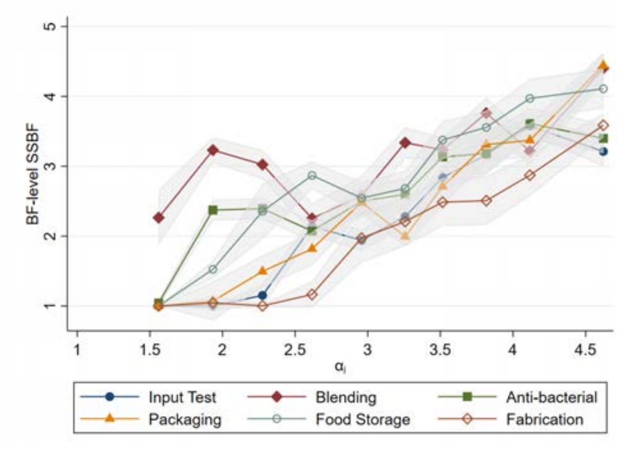


(b) $\phi = 1$

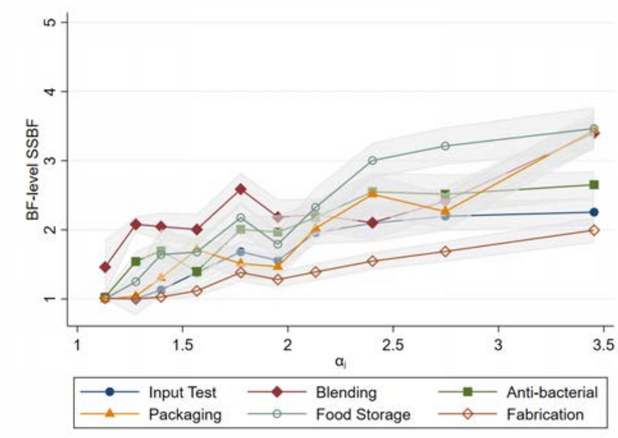


(c) $\phi = 3$

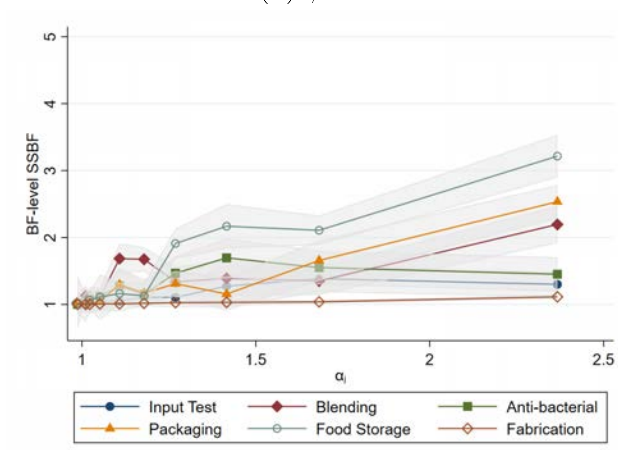
Figure G.2: Robustness of The Technology Curve, $s_{f,j}$ vs. α_j by Deciles, Agriculture



(a) $\phi = 1/3$

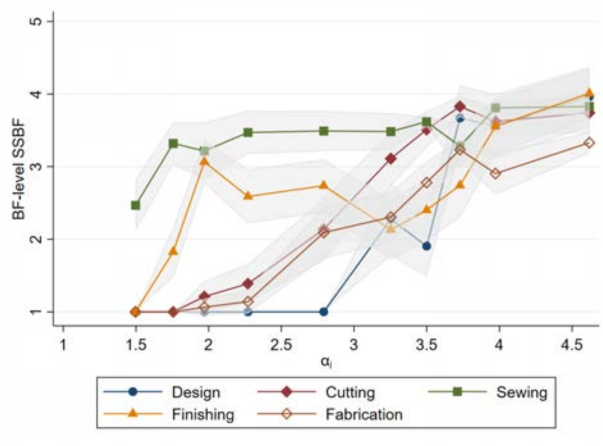


(b) $\phi = 1$

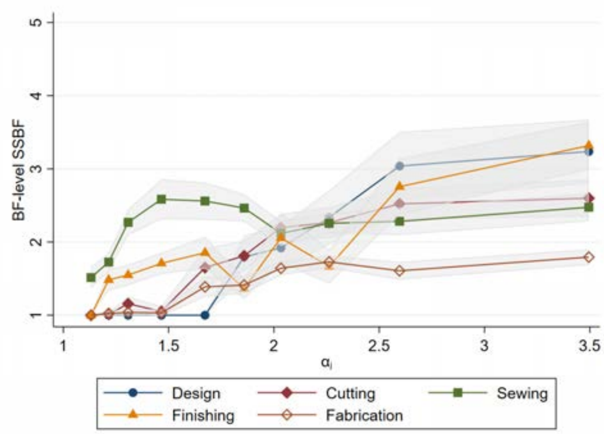


(c) $\phi = 3$

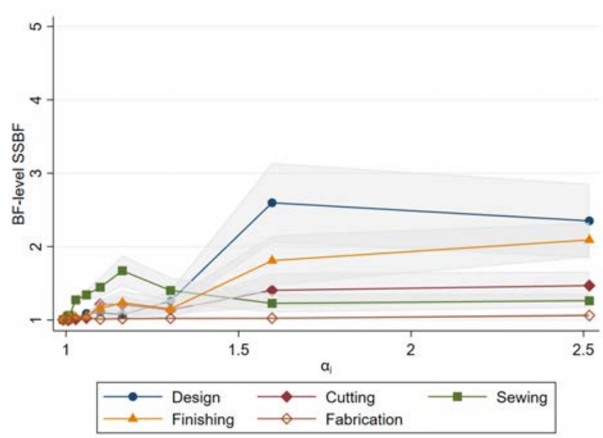
Figure G.3: Robustness of The Technology Curve, $s_{f,j}$ vs. α_j by Deciles, Food Processing



(a) $\phi = 1/3$

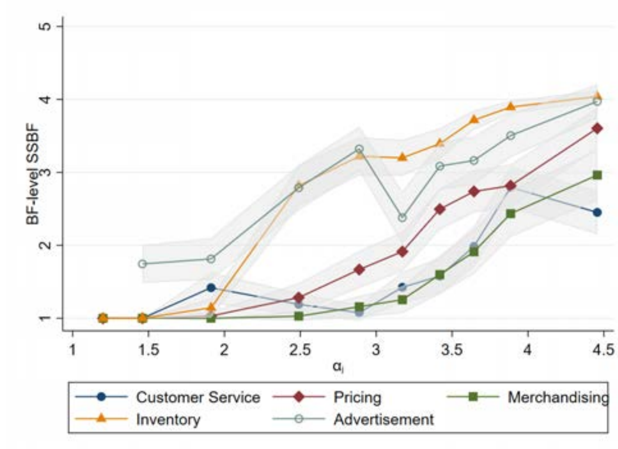


(b) $\phi = 1$

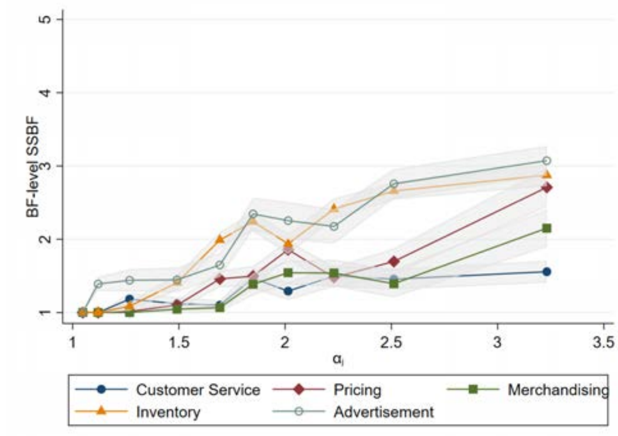


(c) $\phi = 3$

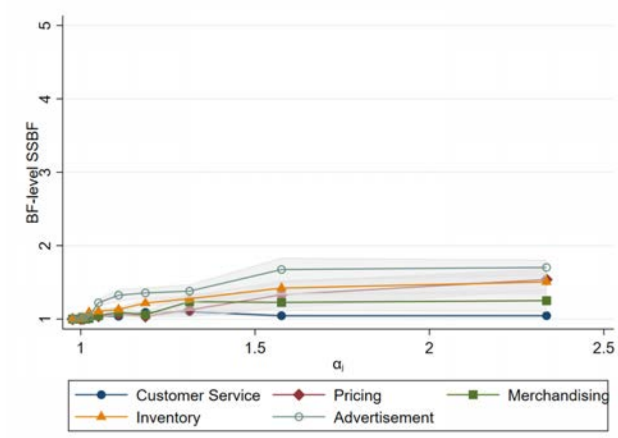
Figure G.4: Robustness of The Technology Curve, $s_{f,j}$ vs. α_j by Deciles, Wearing Apparel



(a) $\phi = 1/3$



(b) $\phi = 1$



(c) $\phi = 3$

Figure G.5: Robustness of The Technology Curve, $s_{f,j}$ vs. α_j by Deciles, Wholesale and Retail

Table G.1: Robustness of Pairwise Correlation: Technology Sophistication and Firm Characteristics

	ϕ=1/3	ϕ=1/2	ϕ=2/3	ϕ=1.5	ϕ=2	ϕ=3
Size	0.18*	0.19*	0.21*	0.23*	0.23*	0.23*
Export	0.29*	0.30*	0.30*	0.29*	0.27*	0.25*
Foreign-owned	0.30*	0.31*	0.31*	0.28*	0.26*	0.23*
% of professionals	0.21*	0.22*	0.24*	0.27*	0.28*	0.28*
% of workers with college degree	0.23*	0.23*	0.22*	0.19*	0.17*	0.15*
% of workers with engineering or graduate degree	0.20*	0.22*	0.23*	0.25*	0.25*	0.25*
Any R&D	0.22*	0.23*	0.24*	0.26*	0.26*	0.25*
Ln(average wage)	0.13*	0.14*	0.15*	0.17*	0.17*	0.18*

Note: * $p < 0.05$. The pairwise correlations between technology sophistication and each proxy variable for the use of advanced technologies is estimated after partialling out country and sector dummies (Agriculture, Manufacturing, and Services). Estimates are weighted by the sampling weights.

Table G.2: Robustness of Average Technology Sophistication by Country

	$\phi = 1/3$			$\phi = 1/2$			$\phi = 2/3$		
	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Overall	2.51	2.57	2.30	2.29	2.35	2.09	2.11	2.17	1.92
Brazil (BR)	2.99	3.17	2.61	2.78	2.96	2.39	2.60	2.78	2.21
Vietnam (VT)	2.86	2.89	2.75	2.54	2.56	2.43	2.28	2.30	2.17
Senegal (SN)	1.67	1.66	1.55	1.54	1.53	1.46	1.44	1.43	1.38
Gap: BR - SN	1.32	1.51	1.07	1.24	1.43	0.94	1.16	1.35	0.82
Relative Gap	33%	38%	27%	31%	36%	23%	29%	34%	21%
	$\phi = 1.5$			$\phi = 2$			$\phi = 3$		
	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Overall	1.61	1.66	1.43	1.46	1.53	1.30	1.32	1.38	1.16
Brazil (BR)	2.06	2.24	1.64	1.89	2.07	1.47	1.69	1.87	1.28
Vietnam (VT)	1.57	1.57	1.48	1.38	1.38	1.30	1.20	1.21	1.14
Senegal (SN)	1.19	1.18	1.17	1.13	1.12	1.12	1.08	1.07	1.06
Gap: BR - SN	0.87	1.06	0.47	0.76	0.95	0.35	0.61	0.80	0.22
Relative Gap	22%	27%	12%	19%	24%	9%	15%	20%	5%

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

Table G.3: Robustness of Cross-Country Average Technology Sophistication of ABF by Sector

	$\phi = 1/3$			$\phi = 1/2$			$\phi = 2/3$		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	2.56	2.43	2.55	2.35	2.20	2.33	2.18	2.01	2.15
Brazil (BR)	3.27	2.87	3.02	3.03	2.62	2.81	2.83	2.42	2.64
Vietnam (VT)	2.84	2.82	2.88	2.57	2.49	2.56	2.35	2.23	2.30
Senegal (SN)	1.56	1.59	1.76	1.45	1.48	1.62	1.37	1.39	1.51
Gap: BR - SN	1.71	1.27	1.26	1.58	1.14	1.19	1.46	1.03	1.13
Relative Gap**	43%	32%	31%	39%	29%	30%	37%	26%	28%
	$\phi = 1.5$			$\phi = 2$			$\phi = 3$		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.69	1.51	1.64	1.55	1.38	1.50	1.39	1.25	1.35
Brazil (BR)	2.21	1.84	2.11	2.02	1.68	1.94	1.80	1.52	1.73
Vietnam (VT)	1.70	1.52	1.58	1.51	1.34	1.39	1.32	1.18	1.21
Senegal (SN)	1.15	1.16	1.23	1.10	1.10	1.16	1.06	1.06	1.10
Gap: BR - SN	1.06	0.69	0.88	0.91	0.58	0.77	0.74	0.46	0.63
Relative Gap**	26%	17%	22%	23%	14%	19%	18%	12%	16%

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. Overall is the average of Brazil, Vietnam, and Senegal. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 $((Brazil - Senegal)/Maximum\ Gap\ (4))$. Technology measures are weighted by the sampling weights.

Table G.4: Robustness of Cross-Country Average Technology Sophistication of GBF by Sector

	$\phi = 1/3$			$\phi = 1/2$			$\phi = 2/3$		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	2.41	2.41	2.66	2.19	2.19	2.43	2.01	2.01	2.24
Brazil (BR)	3.08	2.84	3.26	2.83	2.61	3.05	2.62	2.43	2.87
Vietnam (VT)	2.71	2.85	2.90	2.40	2.52	2.58	2.15	2.26	2.31
Senegal (SN)	1.44	1.55	1.80	1.34	1.44	1.66	1.26	1.35	1.54
Gap: BR - SN	1.64	1.29	1.45	1.49	1.18	1.39	1.36	1.08	1.33
Relative Gap**	41%	32%	36%	37%	29%	35%	34%	27%	33%
	$\phi = 1.5$			$\phi = 2$			$\phi = 3$		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.53	1.53	1.72	1.41	1.40	1.57	1.30	1.28	1.42
Brazil (BR)	2.05	1.90	2.33	1.89	1.75	2.16	1.73	1.59	1.95
Vietnam (VT)	1.47	1.55	1.58	1.30	1.36	1.39	1.14	1.19	1.21
Senegal (SN)	1.08	1.13	1.24	1.05	1.09	1.17	1.03	1.05	1.11
Gap: BR - SN	0.96	0.77	1.09	0.84	0.66	0.99	0.70	0.54	0.84
Relative Gap**	24%	19%	27%	21%	17%	25%	18%	14%	21%

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. Overall is the average of Brazil, Vietnam, and Senegal. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 ($(Brazil - Senegal)/Maximum\ Gap\ (4)$). Technology measures are weighted by the sampling weights.

Table G.5: Robustness of Cross-Country Average Technology Sophistication of SSBF by Sector

	$\phi = 1/3$			$\phi = 1/2$			$\phi = 2/3$		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	2.72	2.35	2.25	2.55	2.10	2.07	2.41	1.89	1.91
Brazil (BR)	3.55	2.86	2.49	3.32	2.54	2.30	3.13	2.29	2.14
Vietnam (VT)	2.86	2.66	2.80	2.70	2.30	2.50	2.56	2.03	2.25
Senegal (SN)	1.75	1.54	1.47	1.63	1.45	1.40	1.53	1.37	1.34
Gap: BR - SN	1.80	1.31	1.02	1.69	1.09	0.90	1.59	0.92	0.80
Relative Gap**	45%	33%	25%	42%	27%	23%	40%	23%	20%
	$\phi = 1.5$			$\phi = 2$			$\phi = 3$		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.92	1.36	1.45	1.75	1.24	1.31	1.53	1.13	1.17
Brazil (BR)	2.46	1.60	1.63	2.21	1.43	1.46	1.91	1.27	1.27
Vietnam (VT)	2.04	1.33	1.55	1.84	1.18	1.36	1.58	1.07	1.18
Senegal (SN)	1.26	1.15	1.17	1.18	1.10	1.12	1.11	1.05	1.07
Gap: BR - SN	1.20	0.45	0.47	1.03	0.33	0.34	0.80	0.22	0.19
Relative Gap**	30%	11%	12%	26%	8%	9%	20%	6%	5%

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. Overall is the average of Brazil, Vietnam, and Senegal. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 $((Brazil - Senegal)/Maximum\ Gap\ (4))$. Technology measures are weighted by the sampling weights.

Table G.6: Robustness of Cross-Firm Variance in Technology Sophistication

	$\phi = 1/3$			$\phi = 1/2$			$\phi = 2/3$		
	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
$Var(S_c - S)$	0.35	0.43	0.30	0.29	0.36	0.21	0.24	0.31	0.15
$Var(s_j - S_c)$	0.35	0.38	0.73	0.29	0.33	0.53	0.25	0.29	0.41
$Var(s_{j,Brazil} - S_{Brazil})$	0.47	0.54	0.85	0.43	0.51	0.66	0.40	0.50	0.54
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.29	0.30	0.79	0.23	0.24	0.55	0.18	0.19	0.40
$Var(s_{j,Senegal} - S_{Senegal})$	0.29	0.31	0.55	0.23	0.24	0.40	0.18	0.19	0.29
Contribution_within_country	0.50	0.47	0.71	0.51	0.48	0.72	0.52	0.49	0.73
Within country-controls	0.43	0.40	0.66	0.43	0.41	0.67	0.44	0.41	0.69
	$\phi = 1.5$			$\phi = 2$			$\phi = 3$		
	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
$Var(S_c - S)$	0.12	0.19	0.04	0.10	0.15	0.02	0.07	0.12	0.01
$Var(s_j - S_c)$	0.16	0.22	0.18	0.14	0.20	0.13	0.11	0.17	0.10
$Var(s_{j,Brazil} - S_{Brazil})$	0.32	0.46	0.29	0.30	0.45	0.24	0.26	0.42	0.18
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.09	0.10	0.15	0.07	0.08	0.10	0.05	0.05	0.07
$Var(s_{j,Senegal} - S_{Senegal})$	0.08	0.09	0.09	0.06	0.07	0.06	0.04	0.05	0.04
Contribution_within_country	0.57	0.54	0.82	0.60	0.56	0.87	0.63	0.60	0.92
Within country-controls	0.49	0.46	0.77	0.52	0.49	0.82	0.56	0.53	0.89

Note: Technology measures are weighted by the sampling weights. Contribution within with controls is estimated after controlling for size group small, medium and large), sector (agriculture, manufacturing and services), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status.

Table G.7: Robustness of Technology Sophistication and Firm Characteristics

	$\phi = 1/3$			$\phi = 1/2$			$\phi = 2/3$		
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Vietnam	-0.13***	-0.26***	0.12***	-0.23***	-0.37***	0.03	-0.31***	-0.45***	-0.03
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Senegal	-1.23***	-1.36***	-1.08***	-1.15***	-1.28***	-0.93***	-1.07***	-1.21***	-0.81***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Manufacturing	-0.06	0.06	-0.36***	-0.07	0.05	-0.37***	-0.08*	0.05	-0.37***
	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)
Services	0.06	0.36***	-0.40***	0.06	0.34***	-0.35***	0.05	0.33***	-0.32***
	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)
Medium	0.27***	0.28***	0.19***	0.25***	0.26***	0.16***	0.23***	0.25***	0.13***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Large	0.61***	0.64***	0.50***	0.59***	0.63***	0.45***	0.57***	0.62***	0.40***
	(0.04)	(0.04)	(0.07)	(0.04)	(0.04)	(0.06)	(0.03)	(0.04)	(0.05)
Age 6 to 10	-0.00	0.00	0.04	-0.01	-0.01	0.03	-0.01	-0.02	0.02
	(0.03)	(0.03)	(0.05)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.04)
Age 11 to 15	0.01	0.03	0.05	0.00	0.02	0.03	-0.00	0.01	0.01
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
Age 16+	0.02	0.04	0.05	0.02	0.04	0.04	0.02	0.04	0.03
	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
Foreign Owned	0.41***	0.42***	0.50***	0.36***	0.37***	0.40***	0.32***	0.33***	0.33***
	(0.04)	(0.04)	(0.08)	(0.04)	(0.04)	(0.06)	(0.03)	(0.04)	(0.06)
Exporter	0.17***	0.16***	0.17***	0.16***	0.15***	0.14***	0.15***	0.14***	0.13***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)
R^2	0.57	0.60	0.34	0.57	0.60	0.33	0.56	0.59	0.32

	$\phi = 1.5$			$\phi = 2$			$\phi = 3$		
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Vietnam	-0.48***	-0.63***	-0.15***	-0.49***	-0.65***	-0.15***	-0.47***	-0.63***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Senegal	-0.79***	-0.94***	-0.44***	-0.68***	-0.84***	-0.33***	-0.55***	-0.70***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Manufacturing	-0.08**	0.03	-0.32***	-0.07**	0.03	-0.28***	-0.05*	0.02	-0.21***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
Services	0.04	0.27***	-0.22***	0.04	0.24***	-0.19***	0.03	0.20***	-0.16***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
Medium	0.17***	0.20***	0.06***	0.15***	0.18***	0.04**	0.12***	0.15***	0.02
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Large	0.48***	0.55***	0.26***	0.44***	0.51***	0.21***	0.38***	0.46***	0.16***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Age 6 to 10	-0.02	-0.03	-0.01	-0.02	-0.04*	-0.01	-0.03*	-0.04**	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age 11 to 15	-0.03	-0.03	-0.01	-0.03*	-0.04**	-0.01	-0.04**	-0.06***	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age 16+	0.01	0.02	0.01	0.01	0.02	0.01	0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Foreign Owned	0.18***	0.20***	0.12***	0.14***	0.15***	0.07**	0.09***	0.10***	0.02
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Exporter	0.11***	0.10***	0.08***	0.10***	0.09***	0.07***	0.08***	0.07***	0.05***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R^2	0.52	0.55	0.24	0.49	0.52	0.19	0.45	0.48	0.12

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Robust standard errors in parenthesis.

Table G.8: Robustness of Within-firm Variance in Technology Sophistication

	$\phi = 1/3$				$\phi = 1$				$\phi = 3$			
	All	Brazil	Vietnam	Senegal	All	Brazil	Vietnam	Senegal	All	Brazil	Vietnam	Senegal
$Var(T_{f,j,c} - T_{f,c} - T_{j,c})$	1.04	1.36	1.15	0.62	0.56	0.93	0.48	0.26	0.36	0.77	0.19	0.12
$Var(T_{j,c} - T_c)$	0.35	0.47	0.29	0.29	0.20	0.36	0.13	0.12	0.11	0.26	0.05	0.04

Note: Technology measures are weighted by the sampling weights.

Table G.9: Robustness of Within-Firm Variance in Technology Sophistication and Firm Characteristics

	$WVar_j$					
VARIABLES	$\phi = 1/3$	$\phi = 1/2$	$\phi = 2/3$	$\phi = 1.5$	$\phi = 2$	$\phi = 3$
s_j	2.91***	2.23***	1.82***	1.41***	1.22***	0.99***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)
s_j^2	-0.54***	-0.43***	-0.35***	-0.22***	-0.14***	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Vietnam	-0.35***	-0.41***	-0.41***	-0.28***	-0.22***	-0.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Senegal	-0.30***	-0.30***	-0.26***	-0.14***	-0.13***	-0.11***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Manufacturing	0.00	0.00	0.01	0.03	0.04	0.03
	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Services	0.01	0.01	0.00	-0.03	-0.04	-0.05
	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Medium	-0.00	-0.01	-0.01	-0.03**	-0.03**	-0.03**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Large	0.14***	0.11***	0.08**	0.01	-0.01	-0.05*
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Age 6 to 10	0.07**	0.06**	0.05**	0.03*	0.03*	0.03**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age 11 to 15	0.04	0.01	0.00	-0.01	-0.01	0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age 16+	0.06**	0.05**	0.04**	0.01	0.01	0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Foreign Owned	0.01	0.01	0.01	0.02	0.02	0.01
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Exporter	0.08***	0.07***	0.06***	0.06***	0.06***	0.07***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	3,893	3,893	3,893	3,893	3,893	3,893
R-squared	0.41	0.38	0.38	0.50	0.54	0.62

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Robust standard errors in parentheses.

Table G.10: Robustness of Productivity and Technology Sophistication ($\Phi = 1/3$)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.59***	2.40***	0.58***		1.19**	1.39***
	(0.08)	(0.41)	(0.08)		(0.52)	(0.52)
s_j^2		-0.34***			-0.11	-0.08
		(0.07)			(0.09)	(0.09)
SD_j			0.85***		0.75***	1.74***
			(0.12)		(0.15)	(0.37)
a_j				0.63***		
				(0.08)		
$s_j \times SD_j$						-0.40***
						(0.13)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.48	0.49	0.50	0.49	0.50	0.51

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.11: Robustness of Productivity and Technology Sophistication ($\Phi = 1/2$)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.65***	2.54***	0.61***		1.53***	1.64***
	(0.09)	(0.44)	(0.09)		(0.53)	(0.53)
s_j^2		-0.38***			-0.18*	-0.12
		(0.08)			(0.10)	(0.11)
SD_j			0.87***		0.74***	1.92***
			(0.13)		(0.16)	(0.42)
a_j				0.69***		
				(0.09)		
$s_j \times SD_j$						-0.51***
						(0.16)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.48	0.49	0.50	0.49	0.50	0.51

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.12: Robustness of Productivity and Technology Sophistication ($\Phi = 2/3$)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.69***	2.66***	0.61***		1.84***	1.84***
	(0.09)	(0.46)	(0.10)		(0.54)	(0.56)
s_j^2		-0.41***			-0.25**	-0.15
		(0.09)			(0.10)	(0.12)
SD_j			0.84***		0.69***	2.03***
			(0.14)		(0.16)	(0.46)
a_j				0.72***		
				(0.09)		
$s_j \times SD_j$						-0.61***
						(0.18)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.48	0.49	0.50	0.49	0.50	0.50

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.13: Robustness of Productivity and Technology Sophistication ($\Phi = 1.5$)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.73***	2.76***	0.55***		2.30***	1.98***
	(0.11)	(0.52)	(0.13)		(0.62)	(0.69)
s_j^2		-0.51***			-0.42***	-0.20
		(0.11)			(0.13)	(0.18)
SD_j			0.54***		0.39**	1.57***
			(0.16)		(0.17)	(0.55)
a_j				0.72***		
				(0.10)		
$s_j \times SD_j$						-0.66***
						(0.25)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.48	0.48	0.48	0.48	0.48	0.49

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.14: Robustness of Productivity and Technology Sophistication ($\Phi = 2.0$)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.71***	2.65***	0.52***		2.28***	1.90***
	(0.11)	(0.54)	(0.14)		(0.63)	(0.70)
s_j^2		-0.51***			-0.45***	-0.21
		(0.13)			(0.14)	(0.20)
SD_j			0.44***		0.32*	1.32**
			(0.16)		(0.17)	(0.54)
a_j				0.68***		
				(0.10)		
$s_j \times SD_j$						-0.60**
						(0.27)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.47	0.48	0.47	0.47	0.48	0.48

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.15: Robustness of Productivity and Technology Sophistication ($\Phi = 3.0$)

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.66***	2.57***	0.48***		2.30***	1.88**
	(0.12)	(0.59)	(0.17)		(0.67)	(0.73)
s_j^2		-0.53***			-0.50***	-0.20
		(0.15)			(0.15)	(0.22)
SD_j			0.33*		0.24	1.18**
			(0.17)		(0.17)	(0.55)
a_j				0.62***		
				(0.10)		
$s_j \times SD_j$						-0.62**
						(0.30)
Firm Characteristics	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.47	0.47	0.47	0.47	0.47	0.47

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.16: Robustness of Productivity and Technology Sophistication ($\Phi = 1/3$), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.57***	0.58***	
	(0.08)	(0.08)	
s_j^{GBF}*Agriculture			0.61**
			(0.24)
s_j^{GBF}*Manufacturing			0.55***
			(0.08)
s_j^{GBF}*Services			0.59***
			(0.10)
s_j^{SSBF}*Agriculture	0.38**		
	(0.16)		
s_j^{SSBF}*Manufacturing	0.16***		
	(0.05)		
s_j^{SSBF}*Services	-0.04		
	(0.09)		
s_j^{SSBF}*Agriculture		0.39**	0.37**
		(0.16)	(0.17)
s_j^{SSBF}*Food Processing		0.27**	0.28**
		(0.12)	(0.12)
s_j^{SSBF}*Apparel		0.47***	0.49***
		(0.09)	(0.10)
s_j^{SSBF}*Retail and Wholesale		-0.06	-0.07
		(0.09)	(0.10)
s_j^{SSBF}*Other Manufacturing		0.08	0.09*
		(0.05)	(0.05)
SD_j	0.87***	0.86***	0.86***
	(0.12)	(0.12)	(0.12)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.51	0.51	0.51

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.17: Robustness of Productivity and Technology Sophistication ($\Phi = 1/2$), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.59***	0.60***	
	(0.09)	(0.09)	
s_j^{GBF}*Agriculture			0.60**
			(0.26)
s_j^{GBF}*Manufacturing			0.60***
			(0.09)
s_j^{GBF}*Services			0.60***
			(0.11)
s_j^{SSBF}*Agriculture	0.43***		
	(0.17)		
s_j^{SSBF}*Manufacturing	0.19***		
	(0.05)		
s_j^{SSBF}*Services	-0.06		
	(0.11)		
s_j^{SSBF}*Agriculture		0.44***	0.44**
		(0.17)	(0.18)
s_j^{SSBF}*Food Processing		0.31**	0.31**
		(0.14)	(0.14)
s_j^{SSBF}*Apparel		0.53***	0.53***
		(0.11)	(0.11)
s_j^{SSBF}*Retail and Wholesale		-0.08	-0.08
		(0.11)	(0.11)
s_j^{SSBF}*Other Manufacturing		0.09	0.09
		(0.06)	(0.06)
SD_j	0.88***	0.87***	0.87***
	(0.13)	(0.13)	(0.14)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.51	0.51	0.51

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.18: Robustness of Productivity and Technology Sophistication ($\Phi = 2/3$), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.58***	0.59***	
	(0.09)	(0.09)	
s_j^{GBF}*Agriculture			0.56**
			(0.28)
s_j^{GBF}*Manufacturing			0.63***
			(0.10)
s_j^{GBF}*Services			0.58***
			(0.11)
s_j^{SSBF}*Agriculture	0.49***		
	(0.18)		
s_j^{SSBF}*Manufacturing	0.22***		
	(0.06)		
s_j^{SSBF}*Services	-0.06		
	(0.12)		
s_j^{SSBF}*Agriculture		0.50***	0.51***
		(0.18)	(0.19)
s_j^{SSBF}*Food Processing		0.35**	0.33**
		(0.16)	(0.16)
s_j^{SSBF}*Apparel		0.58***	0.56***
		(0.12)	(0.13)
s_j^{SSBF}*Retail and Wholesale		-0.09	-0.08
		(0.13)	(0.13)
s_j^{SSBF}*Other Manufacturing		0.11	0.10
		(0.07)	(0.07)
SD_j	0.84***	0.83***	0.83***
	(0.14)	(0.14)	(0.15)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.50	0.50	0.50

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.19: Robustness of Productivity and Technology Sophistication ($\Phi = 1.5$), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.48***	0.49***	
	(0.11)	(0.11)	
s_j^{GBF}*Agriculture			0.34
			(0.29)
s_j^{GBF}*Manufacturing			0.72***
			(0.13)
s_j^{GBF}*Services			0.45***
			(0.12)
s_j^{SSBF}*Agriculture	0.75***		
	(0.25)		
s_j^{SSBF}*Manufacturing	0.29***		
	(0.11)		
s_j^{SSBF}*Services	-0.08		
	(0.20)		
s_j^{SSBF}*Agriculture		0.76***	0.85***
		(0.25)	(0.25)
s_j^{SSBF}*Food Processing		0.48**	0.40*
		(0.23)	(0.23)
s_j^{SSBF}*Apparel		0.69***	0.59***
		(0.20)	(0.20)
s_j^{SSBF}*Retail and Wholesale		-0.15	-0.09
		(0.21)	(0.22)
s_j^{SSBF}*Other Manufacturing		0.13	0.06
		(0.10)	(0.08)
SD_j	0.53***	0.53***	0.49***
	(0.16)	(0.16)	(0.16)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.48	0.48	0.49

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.20: Robustness of Productivity and Technology Sophistication ($\Phi = 2.0$), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.43***	0.45***	
	(0.12)	(0.12)	
s_j^{GBF}*Agriculture			0.26
			(0.28)
s_j^{GBF}*Manufacturing			0.75***
			(0.14)
s_j^{GBF}*Services			0.39***
			(0.13)
s_j^{SSBF}*Agriculture	0.86***		
	(0.30)		
s_j^{SSBF}*Manufacturing	0.25**		
	(0.12)		
s_j^{SSBF}*Services	-0.07		
	(0.23)		
s_j^{SSBF}*Agriculture		0.87***	0.99***
		(0.30)	(0.29)
s_j^{SSBF}*Food Processing		0.52**	0.41
		(0.25)	(0.25)
s_j^{SSBF}*Apparel		0.68***	0.56**
		(0.23)	(0.23)
s_j^{SSBF}*Retail and Wholesale		-0.16	-0.08
		(0.25)	(0.26)
s_j^{SSBF}*Other Manufacturing		0.08	0.02
		(0.08)	(0.07)
SD_j	0.45***	0.44***	0.39**
	(0.16)	(0.17)	(0.17)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.48	0.48	0.48

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.21: Robustness of Productivity and Technology Sophistication ($\Phi = 3.0$), Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.35***	0.37***	
	(0.13)	(0.13)	
s_j^{GBF}*Agriculture			0.22
			(0.27)
s_j^{GBF}*Manufacturing			0.77***
			(0.16)
s_j^{GBF}*Services			0.30**
			(0.14)
s_j^{SSBF}*Agriculture	1.01***		
	(0.37)		
s_j^{SSBF}*Manufacturing	0.17		
	(0.11)		
s_j^{SSBF}*Services	0.01		
	(0.29)		
s_j^{SSBF}*Agriculture		1.02***	1.14***
		(0.37)	(0.37)
s_j^{SSBF}*Food Processing		0.57**	0.43
		(0.27)	(0.26)
s_j^{SSBF}*Apparel		0.61**	0.49*
		(0.28)	(0.27)
s_j^{SSBF}*Retail and Wholesale		-0.13	-0.01
		(0.32)	(0.33)
s_j^{SSBF}*Other Manufacturing		0.01	-0.04
		(0.06)	(0.05)
SD_j	0.35**	0.34*	0.28
	(0.17)	(0.17)	(0.17)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.47	0.47	0.47

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

G.2 Controlling for 4-digit sector-level dummies

This section presents some robustness check we conducted for our main results controlling for a very disaggregated sectoral level. In the main text, we estimated specifications where we include either aggregated sectors dummies (e.g., Agriculture, Manufacturing, and Services) or dummies based on the 10 sectors used in the sectoral stratification. These are relatively aggregated levels of economic activity. Given the broad scope of the firms in the sample, and the possibility that some of the variables of interest are correlated in the cross-section with thinner sectoral disaggregations, we re-examine the key cross-firm results controlling for 4-digit ISIC sector dummies. The firms in our sample belong to 227 different 4-digit sectors. Specifically, Agriculture, Manufacturing, and Services include 24, 109, and 94 different 4-digit sectors, respectively. ISIC 4-digit sectors provide a fine mapping to the specific products and services produced by a firm. For example, in Agriculture, the 4-digit sectors include growing of cereals (except rice), leguminous crops and oil seeds, growing of vegetables and melons, roots and tubers, growing of sugar cane, growing of other non-perennial crops, growing of grapes, growing of tropical and subtropical fruits, growing of other tree and bush fruits and nuts, growing of beverage crops, growing of spices, aromatic, drug and pharmaceutical crops, growing of other perennial crops, and plant propagation. Given this level of detail, controlling by the 4-digit sector where a firm operates can reduce the concerns that variation in the composition of sub-sectors along certain dimensions (e.g., technology sophistication) might be influencing our main findings.

In Table G.22, we examine if the association between technology sophistication and observable firm characteristics are robust to controlling for 4-digit sectors. Table G.23 re-examines the relationship between within-firm variance in sophistication, average technology sophistication and other firm characteristics including 4-digit sector dummies. Finally, we estimate the productivity regressions including 4-digit sector dummies. The productivity regressions results on ABF are presented in Tables G.24, G.25, and G.26. The results where we allow for different coefficients in GBFs and SSBFs are provided in Tables G.27, G.28, and G.29.

Overall, results show that the relationships between sophistication and firm characteristics, between within-firm variance and technology sophistication, and between productivity and firm sophistication measures are robust to including dummies that capture more disaggregated sectoral classifications.

Table G.22: Technology Sophistication and Firm Characteristics Controlling for 4-digit Industry Dummies

	(1)	(2)	(3)
		s_j	
VARIABLES	ABF	GBF	SSBF
Vietnam	-0.49***	-0.63***	-0.12***
	(0.02)	(0.02)	(0.03)
Senegal	-0.93***	-1.04***	-0.68***
	(0.02)	(0.02)	(0.03)
Medium	0.22***	0.25***	0.12***
	(0.02)	(0.02)	(0.02)
Large	0.53***	0.60***	0.35***
	(0.03)	(0.03)	(0.04)
Age 6 to 10	-0.03	-0.04*	0.03
	(0.02)	(0.02)	(0.03)
Age 11 to 15	-0.02	-0.03	-0.01
	(0.02)	(0.02)	(0.03)
Age 16+	0.02	0.02	0.04*
	(0.02)	(0.02)	(0.03)
Foreign Owned	0.27***	0.27***	0.22***
	(0.03)	(0.03)	(0.04)
Exporter	0.09***	0.08***	0.08***
	(0.02)	(0.02)	(0.03)
4-digit Industry	√	√	√
Observations	3,896	3,896	3,076
R-squared	0.65	0.67	0.48

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Robust standard errors in parentheses.

Table G.23: Within-Firm Variance in Technology Sophistication and Firm Characteristics Controlling for 4-digit Industry Dummies

	(1)	(2)	(3)
		$WVar_j$	
VARIABLES	ABF	GBF	SSBF
s_j	1.54***	1.58***	1.37***
	(0.07)	(0.09)	(0.15)
s_j^2	-0.26***	-0.28***	-0.19***
	(0.02)	(0.02)	(0.04)
Vietnam	-0.30***	-0.40***	0.17***
	(0.02)	(0.03)	(0.05)
Senegal	-0.13***	-0.23***	0.27***
	(0.03)	(0.03)	(0.05)
Medium	-0.04***	-0.02	-0.01
	(0.02)	(0.02)	(0.03)
Large	-0.01	0.01	-0.04
	(0.03)	(0.03)	(0.06)
Age 6 to 10	0.05**	0.02	0.06
	(0.02)	(0.02)	(0.04)
Age 11 to 15	-0.01	-0.04*	0.02
	(0.02)	(0.02)	(0.04)
Age 16+	0.02	-0.00	0.07**
	(0.02)	(0.02)	(0.03)
Foreign owned	-0.02	0.01	0.05
	(0.03)	(0.03)	(0.06)
Exporter	0.05**	0.02	0.04
	(0.02)	(0.02)	(0.03)
4-digit Industry	√	√	√
Observations	3,893	3,888	2,267
R-squared	0.53	0.51	0.28

Note: *** p < 0.01, ** p< 0.05, * p <0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Robust standard errors in parentheses.

Table G.24: Productivity and Technology Sophistication Controlling for 4-digit Industry

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.73***	2.53***	0.56***		1.92***	1.72***
	(0.11)	(0.51)	(0.11)		(0.60)	(0.65)
s_j^2		-0.41***			-0.30**	-0.12
		(0.10)			(0.12)	(0.16)
SD_j			0.67***		0.52***	1.95***
			(0.16)		(0.18)	(0.59)
a_j				0.73***		
				(0.10)		
$s_j \times SD_j$						-0.72***
						(0.26)
Firm Characteristics	√	√	√	√	√	√
4-digit Industry Dummies	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.55	0.56	0.56	0.55	0.56	0.56

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.25: Productivity and Technology Sophistication Controlling for ln(K/L) and 4-digit Industry

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
Ln(K/L)	0.28***	0.28***	0.28***	0.28***	0.27***	0.27***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
s_j	0.54***	2.18***	0.41***		1.68***	1.52**
	(0.11)	(0.55)	(0.12)		(0.63)	(0.68)
s_j^2		-0.37***			-0.28**	-0.13
		(0.11)			(0.12)	(0.16)
SD_j			0.59***		0.46**	1.69***
			(0.17)		(0.19)	(0.62)
a_j				0.55***		
				(0.11)		
$s_j \times SD_j$						-0.61**
						(0.27)
Firm Characteristics	√	√	√	√	√	√
4-digit Industry Dummies	√	√	√	√	√	√
Observations	2,519	2,519	2,519	2,519	2,519	2,519
R-squared	0.59	0.60	0.60	0.60	0.60	0.60

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.26: Productivity and Technology Sophistication Controlling for ln(K/L), ln(Labor Cost/L), and 4-digit Industry

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
Ln(K/L)	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Ln(Labor Cost/L)	0.70***	0.70***	0.70***	0.70***	0.69***	0.69***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
s_j	0.30***	1.61***	0.19*		1.24**	1.16*
	(0.11)	(0.51)	(0.11)		(0.59)	(0.63)
s_j^2		-0.30***			-0.23**	-0.15
		(0.10)			(0.11)	(0.15)
SD_j			0.45***		0.34*	1.02*
			(0.16)		(0.18)	(0.60)
a_j				0.31***		
				(0.10)		
$s_j \times SD_j$						-0.33
						(0.26)
Firm Characteristics	√	√	√	√	√	√
4-digit Industry Dummies	√	√	√	√	√	√
Observations	2,496	2,496	2,496	2,496	2,496	2,496
R-squared	0.64	0.64	0.64	0.64	0.64	0.64

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.27: Productivity and Technology Sophistication Controlling for 4-digit Industry, Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.52***	0.53***	
	(0.10)	(0.10)	
s_j^{GBF}*Agriculture			0.34
			(0.25)
s_j^{GBF}*Manufacturing			0.53***
			(0.11)
s_j^{GBF}*Services			0.54***
			(0.11)
s_j^{SSBF}*Agriculture	0.36***		
	(0.13)		
s_j^{SSBF}*Manufacturing	0.17*		
	(0.09)		
s_j^{SSBF}*Services	0.05		
	(0.11)		
s_j^{SSBF}*Agriculture		0.39***	0.49***
		(0.14)	(0.19)
s_j^{SSBF}*Food Processing		0.19	0.20
		(0.14)	(0.14)
s_j^{SSBF}*Apparel		0.48***	0.48***
		(0.14)	(0.14)
s_j^{SSBF}*Retail and Wholesale		0.02	0.02
		(0.12)	(0.12)
s_j^{SSBF}*Other Manufacturing		-0.00	-0.00
		(0.10)	(0.10)
SD_j	0.67***	0.66***	0.66***
	(0.16)	(0.16)	(0.16)
Firm Characteristics	√	√	√
4-digit Industry Dummies	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.56	0.56	0.56

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.28: Productivity and Technology Sophistication Controlling for ln(K/L) and 4-digit Industry, Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
Ln(K/L)	0.27***	0.27***	0.27***
	(0.04)	(0.04)	(0.04)
s_j^{GBF}	0.36***	0.37***	
	(0.11)	(0.11)	
s_j^{GBF}*Agriculture			0.30
			(0.26)
s_j^{GBF}*Manufacturing			0.40***
			(0.11)
s_j^{GBF}*Services			0.37***
			(0.12)
s_j^{SSBF}*Agriculture	0.18		
	(0.15)		
s_j^{SSBF}*Manufacturing	0.12		
	(0.08)		
s_j^{SSBF}*Services	0.05		
	(0.11)		
s_j^{SSBF}*Agriculture		0.21	0.26
		(0.15)	(0.21)
s_j^{SSBF}*Food Processing		0.07	0.05
		(0.14)	(0.15)
s_j^{SSBF}*Apparel		0.37***	0.36**
		(0.13)	(0.14)
s_j^{SSBF}*Retail and Wholesale		0.02	0.03
		(0.12)	(0.12)
s_j^{SSBF}*Other Manufacturing		0.02	0.01
		(0.09)	(0.10)
SD_j	0.60***	0.59***	0.59***
	(0.17)	(0.17)	(0.17)
Firm Characteristics	√	√	√
4-digit Industry Dummies	√	√	√
Observations	2,519	2,519	2,519
R-squared	0.60	0.60	0.60

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.29: Productivity and Technology Sophistication Controlling for ln(K/L), ln(Labor Cost/L) and 4-digit Industry, Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
Ln(K/L)	0.14***	0.14***	0.14***
	(0.03)	(0.03)	(0.03)
Ln(Labor Cost/L)	0.70***	0.70***	0.70***
	(0.03)	(0.03)	(0.03)
s_j^{GBF}	0.15	0.15	
	(0.10)	(0.10)	
s_j^{GBF}*Agriculture			0.15
			(0.21)
s_j^{GBF}*Manufacturing			0.12
			(0.10)
s_j^{GBF}*Services			0.16
			(0.11)
s_j^{SSBF}*Agriculture	0.09		
	(0.13)		
s_j^{SSBF}*Manufacturing	0.10		
	(0.07)		
s_j^{SSBF}*Services	0.15		
	(0.10)		
s_j^{SSBF}*Agriculture		0.11	0.10
		(0.14)	(0.18)
s_j^{SSBF}*Food Processing		0.07	0.10
		(0.14)	(0.14)
s_j^{SSBF}*Apparel		0.22**	0.23**
		(0.10)	(0.11)
s_j^{SSBF}*Retail and Wholesale		0.15	0.15
		(0.11)	(0.11)
s_j^{SSBF}*Other Manufacturing		0.06	0.07
		(0.07)	(0.08)
SD_j	0.44***	0.43***	0.43***
	(0.16)	(0.16)	(0.16)
Firm Characteristics	√	√	√
4-digit Industry Dummies	√	√	√
Observations	2,496	2,496	2,496
R-squared	0.69	0.69	0.69

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

G.3 Registered firms

This section analyzes the robustness of our results when excluding unregistered firms for Senegal. As discussed in section G.3, the criteria for formality in Senegal are more stringent than in Brazil or Vietnam and, as a result, many of the informal firms in the Senegal would be classified as formal in the other two countries. To be in the sampling frame in Senegal, firms must have at least 5 employees and have a physical address. By having business premises, these establishments are likely to pay at least fees to local governments, which make them comparable with registered firms covered by our sampling frame in Brazil and Vietnam. To be coded as formal, firms in Senegal need to be registered and need to use an accounting system that is compatible with the West African Accounting System (SYSCOA). In contrast, in Brazil and Vietnam the only requisite to be formal is to be registered. In this section we show that our results are robust to restricting the Senegal sample to only formally registered firms, following a definition of informality that is aligned with the International Labor Organization (ILO, 2020).[88]

To begin with, Table G.30 shows that average ranking on technology sophistication across countries follows the same order as observed in Table 1 in the main text. The relative gap between Brazil and Senegal is smaller, suggesting that unregistered firms in Senegal use on average lower levels of technology sophistication. Table G.31 presents a similar finding for aggregated sectors (agriculture, manufacturing, and services) from Table 2.

Table G.32 shows that the cross-firm variance in technology sophistication is significantly larger for the within country component compared to the between country, which are consistent with Table 3 in the main text. Table G.33 shows that the coefficients of the association between technology sophistication and firm characteristics follows the same directions and significance of to results presented in Table 4. Then, Tables G.34 and G.35 show that the results for the within-firm variance are consistent with Tables 5 and 6, respectively. Table G.36 shows the estimations for the technology curve for GBFs using the sample without unregistered Senegal firms. The estimated slope for each business function shows the similar magnitudes as in Table 7.

Finally, Tables G.37 and G.38 show the positive and robust association between productivity and technology sophistication, as highlighted in Tables 9 and 10 of the main text. Table G.39 shows that we obtain similar results for the development accounting exercise as in Table 11.

[88] Our results are also robust if we restrict the Senegal sample further by keeping only formal firms in Senegal, following the National Statistical Agency (ANSD) definition, which also require that the accounting system is compatible with the SYSCOA.

Table G.30: Average Technology Sophistication by Country and Type of Business Function, Registered Firms

	ABF	GBF	SSBF
Overall	1.89	1.95	1.70
Brazil (BR)	2.33	2.51	1.92
Vietnam (VT)	1.91	1.92	1.80
Senegal (SN)	1.43	1.42	1.39
Gap: BR - SN	0.89	1.09	0.54
Relative Gap	22%	27%	13%

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

Table G.31: Cross-Country Average Technology Sophistication by Sector, Registered Firms

	ABF			GBF			SSBF		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.99	1.78	1.92	1.79	1.79	2.01	2.26	1.64	1.71
Brazil (BR)	2.52	2.12	2.38	2.32	2.16	2.60	2.81	1.92	1.89
Vietnam (VT)	2.02	1.86	1.92	1.79	1.89	1.93	2.32	1.64	1.89
Senegal (SN)	1.44	1.37	1.47	1.27	1.32	1.49	1.67	1.37	1.35
Gap: BR - SN	1.08	0.75	0.91	1.05	0.84	1.11	1.14	0.55	0.54
Relative Gap**	27%	19%	23%	26%	21%	28%	28%	14%	14%

Note: AGRI, MANF, and SVC represent agriculture, manufacturing, and services, respectively. Overall is the average of Brazil, Vietnam, and Senegal. For the columns on SSBF, the sample is restricted to the firms having sector-specific technologies. Relative gap is the difference between Brazil and Senegal relative to the maximum technology gap of 4 $((Brazil - Senegal)/Maximum\ Gap\ (4))$. Technology measures are weighted by the sampling weights.

Table G.32: Cross-Firm Variance in Technology Sophistication, Registered Firms

	ABF	GBF	SSBF
$Var(S_c - S)$	0.11	0.17	0.04
$Var(s_j - S_c)$	0.23	0.29	0.30
$Var(s_{j,Brazil} - S_{Brazil})$	0.36	0.48	0.38
$Var(s_{j,Vietnam} - S_{Vietnam})$	0.13	0.14	0.24
$Var(s_{j,Senegal} - S_{Senegal})$	0.19	0.22	0.25
Contribution within	0.68	0.63	0.88
Contribution within with controls	0.57	0.53	0.81

Note: Technology measures are weighted by the sampling weights. Contribution within with controls is estimated after controlling for size group small, medium and large), sector (agriculture, manufacturing and services), age (0-5, 6-10, 11-15, and 16 years or more), export and foreign ownership status.

Table G.33: Technology Sophistication and Firm Characteristics, Registered Firms

	s_j		
VARIABLES	ABF	GBF	SSBF
Vietnam	-0.40***	-0.55***	-0.09***
	(0.02)	(0.02)	(0.03)
Senegal	-0.88***	-1.03***	-0.55***
	(0.02)	(0.03)	(0.03)
Manufacturing	-0.17***	0.02	-0.59***
	(0.05)	(0.06)	(0.06)
Services	-0.01	0.33***	-0.46***
	(0.05)	(0.06)	(0.06)
Medium	0.21***	0.24***	0.10***
	(0.02)	(0.02)	(0.02)
Large	0.54***	0.60***	0.33***
	(0.03)	(0.04)	(0.04)
Age 6 to 10	-0.03	-0.04	-0.01
	(0.02)	(0.03)	(0.03)
Age 11 to 15	-0.03	-0.03	-0.00
	(0.02)	(0.03)	(0.03)
Age 16+	0.02	0.03	0.03
	(0.02)	(0.03)	(0.03)
Foreign Owned	0.25***	0.26***	0.22***
	(0.03)	(0.04)	(0.05)
Exporter	0.14***	0.13***	0.09***
	(0.02)	(0.03)	(0.03)
Observations	3,333	3,333	2,598
R-squared	0.43	0.47	0.19

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Regressions include constant and a dummy for whether a firm has SSBF. Robust standard errors in parentheses.

Table G.34: Within-firm Variance in Technology Sophistication, Registered Firms

	All	Brazil	Vietnam	Senegal
$Var(s_{f,j} - s_f - s_j)$	0.64	0.93	0.48	0.39
$Var(s_j - S_c)$	0.23	0.36	0.13	0.19

Note: Technology measures are weighted by the sampling weights.

Table G.35: Within-Firm Variance in Technology Sophistication and Firm Characteristics, Registered Firms

VARIABLES	$WVar_j$
s_j	1.11***
	(0.08)
s_j^2	-0.19***
	(0.02)
Vietnam	-0.37***
	(0.02)
Senegal	-0.21***
	(0.03)
Manuf	0.04
	(0.05)
SVC	0.03
	(0.05)
Medium	-0.03*
	(0.02)
Large	0.03
	(0.03)
Age 6 to 10	0.06***
	(0.02)
Age 11 to 15	-0.01
	(0.02)
Age 16+	0.03
	(0.02)
MNCs	0.03
	(0.03)
Exporter	0.05**
	(0.02)
Observations	3,330
R-squared	0.34

Note: *** p<0.01, ** p<0.05, * p<0.1. Reference group for country, sector, size, and age categories is Brazil, Agriculture, Small, and Age 0 to 5, respectively. Robust standard errors in parentheses.

Table G.36: Technology Curve for General Business Function, Registered Firms

General Business		Agriculture - Crops		Food Processing		Wearing Apparel		Wholesale & Retail	
ϵ^{β}_{Admin}	1.81***	$\epsilon^{\beta}_{Irrigation}$	1.49***	$\epsilon^{\beta}_{FoodStorage}$	1.04***	$\epsilon^{\beta}_{Design}$	1.02***	$\epsilon^{\beta}_{Advert}$	0.75***
	(0.01)		(0.32)		(0.22)		(0.20)		(0.09)
$\epsilon^{\beta}_{Planning}$	1.64***	$\epsilon^{\beta}_{Storage}$	1.44***	$\epsilon^{\beta}_{Packaging}$	0.88***	$\epsilon^{\beta}_{Cutting}$	0.62***	$\epsilon^{\beta}_{Inventory}$	0.65***
	(0.03)		(0.32)		(0.22)		(0.20)		(0.06)
$\epsilon^{\beta}_{Sourcing}$	1.35***	$\epsilon^{\beta}_{LandPrep}$	1.11***	$\epsilon^{\beta}_{InputTest}$	0.61**	$\epsilon^{\beta}_{Finishing}$	0.43**	$\epsilon^{\beta}_{Pricing}$	0.64***
	(0.03)		(0.31)		(0.25)		(0.21)		(0.06)
$\epsilon^{\beta}_{Quality}$	0.68***	$\epsilon^{\beta}_{Harvest}$	0.93***	$\epsilon^{\beta}_{AntiBact}$	0.46*	$\epsilon^{\beta}_{Fabrication}$	0.03	$\epsilon^{\beta}_{Merchand}$	0.36***
	(0.05)		(0.32)		(0.25)		(0.19)		(0.07)
$\epsilon^{\beta}_{Marketing}$	0.66***	$\epsilon^{\beta}_{PestControl}$	0.82**	$\epsilon^{\beta}_{Blending}$	0.35	$\epsilon^{\beta}_{Sewing}$	-0.06	$\epsilon^{\beta}_{CustomServ}$	0.04
	(0.03)		(0.34)		(0.22)		(0.21)		(0.07)
$\epsilon^{\beta}_{Payment}$	0.51***	$\epsilon^{\beta}_{Packaging}$	0.36	$\epsilon^{\beta}_{Fabrication}$	0.29				
	(0.03)		(0.43)		(0.21)				
ϵ^{β}_{Sales}	0.23***								
	(0.04)								
ϱ	0.16***								
	(0.03)								
Within-firm R^2	0.33								

Note: *** p<0.01, ** p<0.05, * p<0.1. Business function-level technology sophistication is regressed on firm-level technology sophistication using nonlinear least-squares estimation. The parameter ϵ^{β}_{f} for general business functions and ϱ are reported in this table. Standard errors in parentheses.

Table G.37: Productivity and Technology Sophistication, Registered Firms

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)
s_j	0.65***	2.26***	0.57***		1.97***	1.92***
	(0.10)	(0.55)	(0.11)		(0.60)	(0.62)
s_j^2		-0.36***			-0.31***	-0.18
		(0.11)			(0.12)	(0.15)
SD_j			0.47***		0.37**	1.71***
			(0.17)		(0.18)	(0.62)
a_j				0.65***		
				(0.10)		
$s_j \times SD_j$						-0.65**
						(0.26)
Firm Characteristics	√	√	√	√	√	√
Observations	2,466	2,466	2,466	2,466	2,466	2,466
R-squared	0.31	0.32	0.32	0.31	0.32	0.32

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.38: Productivity and Technology Sophistication, Registered Firms, Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
s_j^{GBF}	0.51***	0.52***	
	(0.10)	(0.10)	
s_j^{GBF}*Agriculture			0.48*
			(0.29)
s_j^{GBF}*Manufacturing			0.65***
			(0.11)
s_j^{GBF}*Services			0.49***
			(0.12)
s_j^{SSBF}*Agriculture	1.00***		
	(0.21)		
s_j^{SSBF}*Manufacturing	0.26***		
	(0.08)		
s_j^{SSBF}*Services	0.01		
	(0.16)		
s_j^{SSBF}*Agriculture		1.01***	1.03***
		(0.21)	(0.19)
s_j^{SSBF}*Food Processing		0.39**	0.34**
		(0.16)	(0.16)
s_j^{SSBF}*Apparel		0.69***	0.63***
		(0.19)	(0.19)
s_j^{SSBF}*Retail and Wholesale		-0.03	-0.01
		(0.17)	(0.17)
s_j^{SSBF}*Other Manufacturing		0.13	0.10
		(0.09)	(0.09)
SD_j	0.46***	0.45***	0.43**
	(0.17)	(0.18)	(0.18)
Firm Characteristics	√	√	√
Observations	2,466	2,466	2,466
R-squared	0.32	0.33	0.33

Note: *** p<0.01, ** p<0.05, * p<0.1. The regressions controlled for observable firm characteristics including size (i.e., small, medium, and large), sector (i.e., agriculture crops, livestock, food processing, wearing apparel, pharmaceutical, motor vehicle, wholesale and retail, finance, land transport, hospital, other manufacturing, and other services), age (i.e., 0-5, 6-10, 11-15, and 16 or more), export, and multinational status. Robust standard errors in parentheses.

Table G.39: Development Accounting, Registered Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
P10	-0.34	-0.40	-0.36	-0.37	-0.44	-0.46	-0.38	-0.38	-0.38
P90	0.37	0.35	0.38	0.37	0.38	0.39	0.41	0.43	0.42
% Productivity Dispersion Accounted by Technology	25%	26%	26%	25%	29%	29%	27%	28%	28%

Note: Each row presents development accounting associated with each specification used in Table 9 columns (1)-(6) and Table 10 columns (1)-(3) in order. For each specification, we run regress ln(vapw) and technology measures on firm characteristics to estimate residuals. Then, we run regress the residual of ln(vapw) on the residuals of technology measures and compute P10 and P90 of the predicted outcomes. First and second rows provide the P10 and P90 of the predicted residuals of ln(vapw), respectively. Third row reports as percentages the difference between p90 and p10 of predicted residuals of ln(vapw) divided by the overall difference between between p90 and p10 of the residuals of ln(vapw).

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