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ABSTRACT

We collected data on the sophistication of technologies used at the business function level for a representative sample of firms in Vietnam, Senegal, and the Brazilian state of Ceará. Our analysis finds a large variance in technology sophistication across the business functions of a firm. Specifically, the within-firm variance in technology sophistication is greater than the variance in sophistication across firms, which in turn is greater than the variance in sophistication across regions or countries. We document a stable cross-firm relationship between technology at the business function and firm levels that we name the technology curve. We uncover significant heterogeneity in the slopes of the technology curves across business functions, a finding that is consistent with non-homotheticities in firm-level technology aggregators. Firm productivity is positively associated with the within-firm variance and the average level of technology sophistication. Development accounting exercises show that cross-firm variation in technology accounts for one-third of cross-firm differences in productivity and one-fifth of the agricultural versus non-agricultural gap in cross-country differences in firm productivity.

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1 Introduction

Economists and sociologists have long been interested in studying the technologies involved in production. Going back to the seminal works by Ryan and Gross (1943) and Griliches (1957) on the diffusion of hybrid varieties of corn, the dominant approach to measuring technology has reflected whether a potential adopter uses an advanced technology. In addition to studying technology diffusion (e.g., Mansfield, 1961) and the drivers of adoption (e.g., Foster and Rosenzweig, 1995; Duflo, Kremer and Robinson, 2011; Atkin, Khandelwal and Osman, 2017), this approach has facilitated the study of the effect of technology on productivity (e.g., Bartel, Ichniowski and Shaw, 2007; Juhász, Squicciarini and Voigtländer, 2020) or on wages (e.g., Krueger, 1993; DiNardo and Pischke, 1997). The relevance of these questions has motivated researchers to measure the use of (typically a few) advanced technologies by firms in numerous sectors.[1] Recently, the Canadian "Survey of Advanced Technology" has extended the scope of these measurement efforts to record whether firms use a significant number (between 41 and 50, depending on the round) of advanced technologies. Yet, despite all the progress, existing measures of technology still fall short of providing a comprehensive characterization of technology within firms. From a technological standpoint, firms largely remain black boxes.

For starters, the number of technologies covered is rather limited when compared to how many technologies are involved in production processes. Second, their focus on the presence of advanced technologies makes it impossible to understand how production takes place in companies without such advanced technologies. This concern is most relevant in developing countries where advanced technologies have diffused less. Third, since their unit of analysis is the firm, existing studies are not designed to study what business functions benefit from each technology. This drawback is particularly problematic for general technologies that can be relevant for multiple business functions. Finally, existing surveys largely omit questions about how intensively a technology is employed in the firm, and therefore, they do not reveal whether a technology that is present is widely utilized or just marginally.[2]

To overcome these limitations, this paper pursues a new strategy to measure technology that shifts the unit of analysis from the firm to the business function level. Core to our

[1]For example, Davies (1979) covers 26 manufacturing technologies, 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 assimilated by the statistical offices from advanced economies, including the US Census Bureau (ICTS and ABS), the Eurostat (Community Survey of ICT Usage), and the Statistics Canada (SAT), who have developed ICT surveys for that purpose.

[2]One exception is Mansfield (1963), and the papers that have followed him, which study the diffusion of a technology within a company providing a proxy for the intensity with which the technology is used.

approach is the Firm-level Adoption of Technology (FAT) survey that we have designed and administered to a representative sample of firms in Senegal, Vietnam, and in the Brazilian state of Ceará. With the assistance of a large number of sector and technology experts, we have identified the key business functions and the technologies that companies can use to conduct the main tasks in each of the selected business functions, and have ranked the technologies according to their sophistication. The FAT survey covers seven general business functions (GBF) that are common to all companies regardless of the sector where they operate. In addition, for ten large sectors, we have identified their key sector-specific business functions (SSBF) and the main technologies that can be used. In total, the FAT survey covers 59 business functions and 287 technologies associated with them.[3]

The FAT survey asks firms to list first all the technologies that are used in each business function, and then 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 and of the full array of technologies used in the business function. We use these measures to explore three broad issues: The variation in technology across firms, the patterns of technology use within firms, and the relationship between the sophistication of technology and productivity.

Our analysis reveals large variation in the sophistication of technologies used in production at all levels of aggregation. We document a pattern by which, the variance in sophistication is larger the more disaggregated is the unit of analysis. Specifically, we find greater variance in technology sophistication across the business functions of a firm (i.e., within-firm) than across firms, and greater variance across firms than across countries/regions. Both at the national and regional levels, we document a positive relationship between cross-firm variance in technology sophistication and development. Furthermore, the distribution of average technology sophistication for Brazil shows restricted first-order stochastic dominance (Atkinson, 1987) to the distribution in Vietnam in most of the distribution, which in turn shows restricted stochastic dominance to the distribution in Senegal.

FAT's comprehensive information about the technologies used at the business function level allows to systematically analyze technology within firms. The large within-firm variance in technological sophistication we find debunks the notion that technology is uniform within firms. Within-firm variance increases with the average level of sophistication in the firm and with firm size. We explore the existence of patterns of technology upgrading within the firm by studying how the sophistication of technology in a business function varies with average firm-level sophistication. For each individual business function, we document stable cross-firm relationship between sophistication at the business function level and average firm

[3]See Table A.1 for a comparison with other firm-level surveys.

sophistication. We name this relationship the technology curve. The technology curves have strong predictive power of the cross-firm variation in the sophistication of technology at the business function level, with an average R^2 of 0.39 across business functions. Furthermore, we uncover large heterogeneity across business functions in the slopes of the technology curves. For GBFs, the functions with the steepest technology curves are business administration and planning, while sales has the flattest curve. These findings suggest that a critical driver of within-firm differences in technology is non-homotheticities in production.

Firm-level technology measures are strongly correlated with productivity. We find a positive correlation of average sophistication and productivity. Perhaps more surprisingly, productivity is also positively correlated with the within-firm variance of technology sophistication across business functions after controlling for average firm-level sophistication. We interpret this correlation as evidence of the value for firms of using more sophisticated technologies in the most relevant business functions.

We conclude our analysis by conducting two development accounting exercises that shed light on two classical debates: the drivers of cross-country productivity differences and the much larger cross-country productivity dispersion observed in agriculture than in the productivity of non-agricultural sectors. We estimate that cross-firm differences in technology account for a third of the gap that exists between firms at the top 90% and bottom 10% of the productivity distribution. Cross-country differences in the technology of the average company in agriculture and in non-agricultural activities account for one fifth of the ratio between the cross-country gap in productivity in agricultural firms over the cross-country gap in productivity in non-agricultural firms.

In addition to the studies on technology measurement cited above, our analysis is related to various 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.[4] A third strand of research, closer to ours, has focused on understanding productivity at the firm level, but, unlike us, it considers a reduced number of technologies. 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

[4]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).

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.

There is, however, much less prior work studying technology within firms. To the best of our knowledge, we are the first to study the magnitude of within-firm variance in technology, the relationship between within-firm variance and productivity, to document the existence of technology curves, and the heterogeneity of their slopes across business functions.

Finally, there are interesting parallels between our contribution to measurement of technology and the efforts recently made to measure management practices. There is a long tradition in management and economics documenting and measuring specific management practices in typically a reduced (often just one!) number of companies. 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 countries to measure the quality of management practices along several dimensions connected to operations, planning, monitoring and human resources.[5] Bloom and Van Reenen (2007) compute a firm-level index of management quality as the average of the scores across the 18 dimensions and study how the index relates to firm productivity.

Despite these similarities, there are also important differences between our paper and the literature on management practices. The nature of technologies and management practices are different. While management practices refer to establishing routines to deal with decision processes, technologies are embodied in machines, software or represent processes that typically require certain equipment and technological knowledge. More sophisticated technologies enhance productivity directly, but also indirectly by facilitating and/or inducing the implementation of certain management practices that make a company more productive. Beyond differences in the nature of the objects of study, our survey covers a wider range of business functions - both general and sector-specific - than management studies. This comprehensive coverage of business functions allows us to provide a richer characterization of the technologies used within the firm, which is critical to document the variation in technology sophistication across business functions, to uncover the heterogeneity in the slopes of technology curves across functions, to explore the relationship between within-firm variance in technology and productivity and to identify the sectoral variation in the relationship

[5] These surveys include the World Management Survey (WMS) and the Management and Organizational Practices Survey (MOPS). While the WMS is a telephone based survey, using double blinded methodologies; MOPS is an online and paper based survey.

between technology in sector-specific business functions and productivity.[6]

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 and the advice of the experts to construct our technology sophistication measures. Section 4 analyzes technology across firms. Section 5 analyzes technology within firms. Section 6 studies the relationship between technology and productivity. Section 7 conducts two development accounting exercises and the last section concludes.

2 The Survey

The FAT survey 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 of economic activity. The data assembled with the FAT survey has five desirable properties. First, they provide a granular characterization of productive activities by covering a wide range of technologies both relevant across sectors as well as specific to one. Second, the technologies covered include both advanced and older technologies, so that we can characterize the technological landscape in any firm regardless of its technological sophistication. Third, since the survey is centered at the business function level, it provides information about the technologies used in each business function. Fourth, the questions included in the survey allow us to construct measures that reflect not just the technologies used but also how intensively they are used in conducting the relevant tasks for the business function. Fifth, by covering a wide range of sectors, the data produced by the survey allows for a rich cross-sector characterization of the sophistication of technologies in the economy. In what follows we describe in detail the survey and the process we have followed to design it and implement it (see also Appendix A).

2.1 Structure

The FAT survey is composed of five modules. Module A collects information on general characteristics about the firm.[7] Modules B and C collect information on the technologies used by the firm. Module D collects information on barriers and drivers of technology adoption, while module E gathers information about the firm's balance sheet and output.

The survey differentiates between general business functions (module B) which comprise

[6] One interesting exercise, would be to study whether the sophistication of practices followed by managers within the firm display similar patterns (e.g., technology curves, within-firm variance, and its correlation with average sophistication, firm size, etc.) as those we uncover for technology.

[7] For multi-establishment firms, the survey targets the establishment randomly selected in the sample.

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.[8] These sectors have been selected to represent of all three primary sectors (agriculture, manufacturing, and services) and based on their size in the economies where we have administered the FAT survey, in terms of value-added, employment, and number of establishments.

A key aspect of the design of modules B and C is to determine the business functions and technologies covered in the survey. To this end, we proceeded in three steps. First, we conducted desk research revising the specialized literature. Second, we held meetings with experts across the World Bank Group in each of the sectors covered. Third, we reached out to external consultants with significant experience in the field (at least 15 years).[9] This process helped us identify the main functions, both general and sector-specific, conducted in companies and the technologies that can be used to perform the key tasks in each of the identified functions. Figure 1 presents the general business functions considered in the survey and the possible technologies that can be used to conduct each of them. In total, we consider 7 general business functions and 36 technologies. Similarly, Figure 2 exemplifies with food-processing how module C unpacks sector-specific production activities into the main business functions and the technologies that can be used to accomplish them.[10]

Once we have identified the key business functions and relevant technologies, we use experts' advice to construct measures of technology use at the business function level that go beyond reporting the presence of a given technology. Specifically, sector experts provided information on two key aspects. First, they ranked the technologies in each business functions according to their sophistication.[11] Second, they assessed the degree of substitutability or

[8]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.

[9]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 developing countries and advanced economies.

[10]The Appendix B contains the charts for the other nine SSBFs including agriculture-crops (Figure B.1), livestock (Figure B.2), wearing apparel (Figure B.3), automotive (Figure B.4), pharmaceutical (Figure B.5), wholesale and retail (Figure B.6), transportation (Figure B.7), financial services (Figure B.8), health services (Figure B.9), and other manufacturing (Figure B.10).

[11]Sophistication was defined along several dimensions: quality of the output, productivity, costs, and complexity of operation.

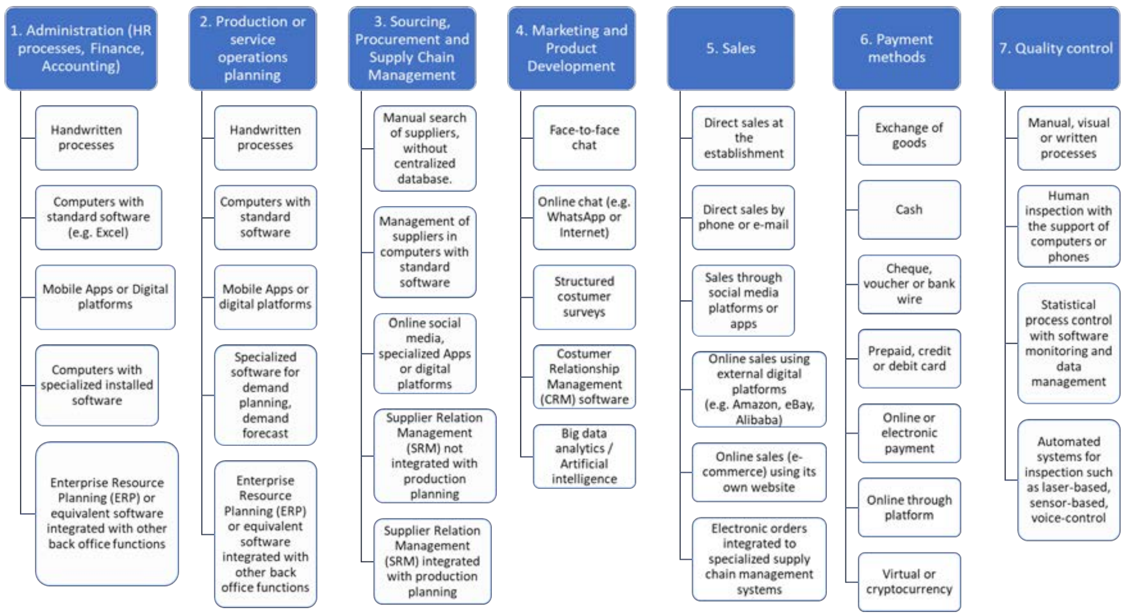


Figure 1: General Business Functions and Their Technologies

complementarity between the technologies that can be used to conduct each task in each business function. As we discuss in the next section, the degree of substitutability between technologies in a business function is important to construct measures of the sophistication of the technologies used in a business function.

2.2 Technology questions

The FAT survey asks two types of questions about the technologies used at a business function. The first one inquires about the use of each of the technologies listed by the experts as relevant in a given business function. The answer to these questions characterize the full array of technologies that the firm uses and, as we discuss in the next section, we employ them to construct measures of the sophistication of the array of technologies used by the firm in a given business function. Note that this approach to gather information about technology has two important advantages. First, by questioning about the full spectrum of technologies, we overcome the problem of not knowing how a firm conducts a business function when it does not use the key advanced technology. Second, by focalizing the survey around the business functions, we automatically learn about the business functions where the firm uses each technology.

The second type of question we have included in the survey to gather information on technology addresses the intensity of use of technology. Specifically, FAT asks what of the

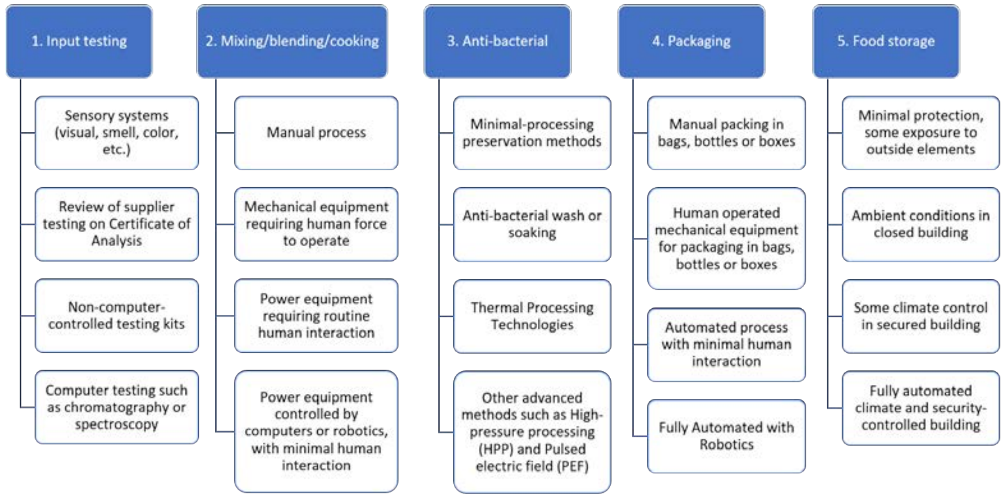


Figure 2: Sector Specific Business Functions and Technologies in Food Processing

relevant technologies in the business function is the one that the firm uses more frequently.[12] We use the answers to this question to construct technology measures that reflect the nature of the main technology in the business function as opposed to the array of technologies available for production. This distinction is relevant because not all the available technologies in a business function are used with the same intensity, and the impact of a technology in the company's productivity surely depends on the importance of the technology used in the business function.

2.3 Sampling and implementation

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.[13] The sample frame includes establishments with five or more employees. The survey is stratified along three dimensions - sector, firm size, and region - so that we can construct representative measures of technology for aggregates along these dimensions.

[12] 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.

[13] Appendix A provides more details on sampling frame (A.1), survey implementation and data collection (A.2), and sampling weight (A.3). 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.

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. The response rate ranges from 39% in Ceará, Brazil, 57% in Senegal to 83% in Vietnam.[14]

To ensure the accuracy in the responses and the comparability of the data collected across countries we use a standardized process for all countries. First, we apply the same questionnaire administered through face-to-face interviews with CAPI (computer-assisted personal interviews) in all countries. Second, we minimize subjective and perception questions when measuring technology, since these are prone to bias.[15] Enumerators were instructed to verify the information provided during the interviews when possible. Third, we conducted a standard training in each country with enumerators, supervisors, and managers leading the data implementation. Fourth, a pre-test pilot of the questionnaire was implemented in each country with firms out of the sample to assure that interviewers clearly understood the questionnaire and data collection was smooth. Fifth, we used the same terms of reference to the organizations that implement the survey across all countries. Finally, the protocol for the implementation of the survey required that the survey should be ideally answered by the top manager. In circumstances in which the main respondent did not have information about a general topic of the questionnaire, especially in modules B and C, they were requested to consult with other colleagues.

Quality control was provided at three stages of the data collection process. First, logical conditions were imposed in CAPI to prevent errors in data inputting.[16] Second, supervisors were required to review all interviews, identifying missing values and abnormal responses. Third, we continuously revised the collected data using standard algorithms to analyze the consistency of the data and provide continuous feedback to assure quality control.

3 Technology Sophistication Measures

The starting point to construct measures of technology at the business function level is the rank of technologies by their sophistication. Let's consider a function f with N_f possible technologies. Based on the experts' assessment we order the technologies in a function according to their sophistication, and assign them a rank $r_i \in 1, 2, ..., R_f$. Because several

[14] In Vietnam, data collection was implemented by the NSO of Vietnam (GSO). In Ceará-Brazil, data collection was implemented by the State Industry Association (FIEC). In Senegal, data collection was implemented by Kantar-public. Appendix A provides the distributions of the universe of firms (Table A.2, Table A.4, Table A.6) and the sample (Table A.3, Table A.5, Table A.7).

[15] See Bertrand and Mullainathan (2001).

[16] For example, a respondent cannot identify a technology not selected as being used as the most frequently used.

technologies may have the same sophistication, the highest rank in a function $R_f \leq N_f$.[17]

Combining the technology rankings with the information collected by the FAT survey on the technologies used by a firm, we construct three indices of technology at the business function level that we denote by MOST, EXT and GAP.

MOST The first index reflects the sophistication of the most widely used technology in a business function, and we call it MOST. The MOST index of a firm j in a business function f is computed as

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

where $r_{f,j}^{MOST}$ is the sophistication rank of the technology identified by the firm as being most widely used for the business function, and R_f is the maximum technology rank in the function. Therefore, the index reflects the technology sophistication of the most widely used technology relative to the most sophisticated technology available in the market to conduct a business function. To no effect, we scale the index so that it is between 1 and 5.

EXT The second index we construct measures the sophistication of the array of technologies used to conduct a business function, and we call it EXT (an abbreviation of extensive). In contrast with MOST, EXT does not reflect how much each technology is used but it reflects the sophistication of all the technologies used in production, rather than just the most relevant one. To measure the sophistication of the range of technologies, we must first understand the degree of substitutability between the technologies in the business function. Figure 3 illustrates four possible structures we encounter in the business functions covered by FAT and that differ in the substitutability between their technologies. Panel A depicts a quality ladder or vertical structure (Aghion and Howitt, 1992). In quality ladders there is no productivity gain from using technologies below the maximum sophistication rank employed in the firm, $r_{f,j}^{MAX}$. Therefore, the sophistication of the technologies employed in business functions with a quality ladder structure is $r_{f,j}^{MAX}$.

The technologies in other business functions may have a horizontal relationship (Romer 1990), depicted in panel B. In horizontal structures, the use of less sophisticated technologies facilitates the fulfillment of the tasks in the function even conditional on using more sophisticated technologies. For example, in marketing the use of less sophisticated technologies

[17] 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.

such as face-to-face communications may allow firms to reach some customers that may not be reachable by more sophisticated technologies such as customer relationship management (CRM) software. The sophistication of the array of technologies used in horizontal structures is measured by the fraction of the possible technologies in the function that the firm uses.

In addition to quality and ladders and horizontal structures, there are other possible hybrid structures between the technologies in a business function that combine these two (see panels C and D, Figure 3). In the Appendix we provide detailed descriptions on these structures, examples of business functions with each structure, and formulas about how we construct the EXT index in each case. As with MOST, we scale the sophistication of technologies employed in a business function by the rank of the most sophisticated technology available,R_f, and normalize EXT so that it is between 1 and 5.

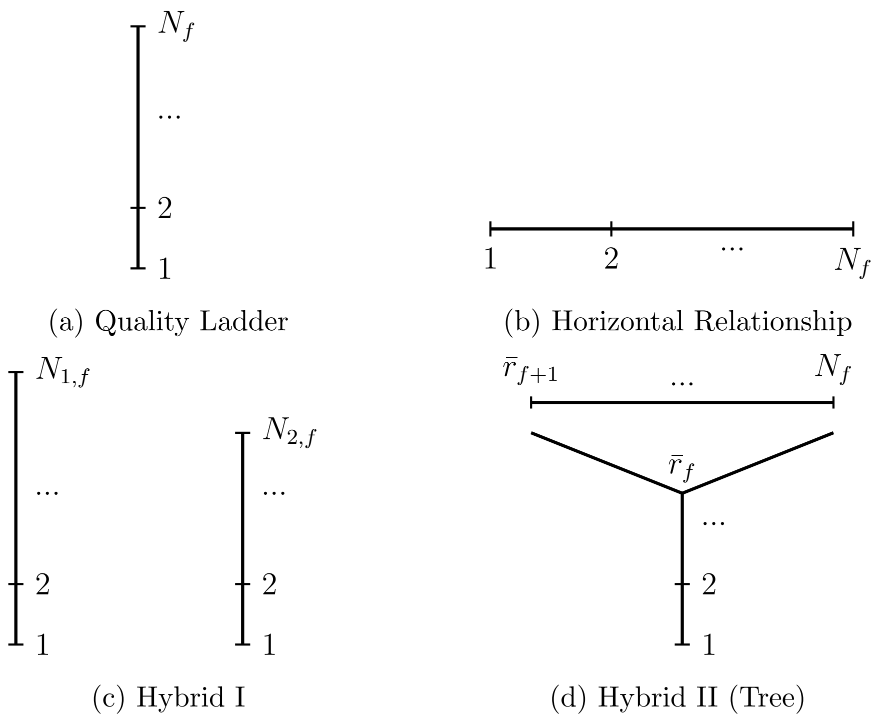


Figure 3: Taxonomy of Structures among the Technologies in a Business Function

GAP To connect EXT and MOST, we introduce GAP as the difference between the sophistication of the array of technologies used (EXT) and the sophistication of the most widely used technology (MOST). GAP reflects the capacity of a firm to occasionally conduct certain tasks of a business function with more sophisticated technologies that those most commonly used in the business function. Consistent with this interpretation, GAP is virtually always positive.[18] The GAP measure opens the possibility of exploring the value for companies of having the flexibility to occasionally use more sophisticated technologies relative to having a more sophisticated technology as the most commonly used.

Discussion Technology rankings are ordinal. However, to make algebraic manipulations and compute statistics it is necessary to treat technology rankings in a cardinal way. This step involves making assumptions about the cardinal increases associated with each jump in the ranking scale. As noted by Thorndike (1966, p.124), "it is assumed that the numerals in which the variables are expressed represent equal increments in some attribute. It is also recognized that this assumption is usually not well supported. But for 'rough and ready' studies of relationship, the violation of the assumption usually does not hurt much." Next, we discuss how we intend to go beyond this imperfect approach to transforming an ordinal relation such as the technology rankings into a cardinal one.

As first discussed by Pareto (1909, p.541-42), Cardinalizations of ordinal rankings are not unique. Furthermore, comparisons of population means based on cardinalizations of ordinal variables may depend on the specific cardinalization unless there is first-order stochastic dominance (FOSD).[19] Fortunately, as we show in section 4.2, the cross-firm distribution of technology sophistication has (restricted) FOSD when comparing bilaterally the countries in our sample. This implies that we could make mean comparisons of firm-level sophistication indices constructed with arbitrary (monotonic) cardinalizations of the technology rankings, including the sophistication indices presented above.

Admittedly, the assumption of constant intervals implicit in the technology indices is arbitrary, but at the same time, it surely is a natural starting point to construct business-function sophistication indices. To begin with, it is consistent with the production structures in the canonical models of endogenous technological change (Romer, 1990; Aghion and Howitt, 1992). Second, as we show in section section 6, indices with constant increments are strongly correlated with (log) labor productivity at the firm level. Furthermore, even though we find that quadratic terms are significant, suggesting the possibility that the best fit would be achieved by a concave technology index (i.e., with diminishing increments), the quadratic term increases very marginally the explanatory power of firm technology implying that indices constructed with constant increments capture reasonably well the relationship between technology sophistication and firm productivity.

Finally, we consider alternative approaches to constructing technology indices. In the

[18] The only exception appears in horizontal structures when the firm does not use some of the technologies below the MOST widely used technology. In these cases, our measure of EXT can be below MOST. This occurs in less than 1% of the firm-business function observations.

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

light of the concave firm-level relationship we uncover between technology and productivity, we explore the robustness of our findings to using a log scale to convert the ordinal technology rankings to business function technology indices. In this way, the scale increases in the technology indices are larger the lower is the technology ranking. We report in the appendix the results from redoing the analyses using this alternative scale increases. The main finding is that our results are completely robust. Given the stark difference in the underlying assumptions about scale increases in the baseline and alternative indices, our conclusions should be robust to other reasonable variations in the mapping used to construct technology sophistication indices at the business function level.

An example We next illustrate how these measures of sophistication can characterize the technological landscape of firms by conducting a case study of two individual firms. Both firms operate in the food processing sector in Senegal, but one has 300 employees while the other only has 20. Figure 4 presents in four spider charts the measures of EXT (right) and MOST (left) for each of the general (top) and sector-specific business functions (bottom) for the two firms (big in dashed blue, small in solid red). In general, the large firm uses more sophisticated technologies than the small one. However, the gap between the sophistication of technologies used in both companies varies considerably depending on the technology measure, the type of business function, and the specific business function we consider.

The top left corner panel shows that, overall, the firm uses a more sophisticated array of technologies in GBFs as measured by EXT. However, while some business functions, such as quality control and sales, there are large differences in the EXT measure between the two firms, in others such as procurement the gap in EXT is much smaller. Additionally, the differences in sophistication of technologies used decline drastically when instead of focusing on the whole array of technologies we restrict our attention to the most widely used technology as measured by MOST. Differences between the two firms in MOST measures for GBFs are small or non-existent. In particular, the value of MOST in both firms is the same in marketing, procurement, production planning and business administration. This suggests that, although the two companies differ in the range of technologies used in production, the sophistication of the main technologies used in GBFs are very similar in both companies.

The comparison for SSBFs is similar. When looking at EXT, the big company has in all business functions higher levels of sophistication than the small one, although the gap varies considerably with larger gaps in input testing, and food storage and smaller gaps in packaging and antibacterial. These differences, however tends to shrink and even reverse when focusing on the sophistication of the most relevant technology in each business function. In particular, the value of MOST in packaging is the same in both companies

Figure 4: 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 indices. The sizes of Firm A and B are 9 and 100 employees, respectively.

and for Mixing/Blending/Cooking the small company has a higher value. One exception to this pattern is Antibacterial where the gap in sophistication in favor of the large company is greater for MOST than for EXT. This illustrates how nuanced is the characterization of technology within companies that the FAT survey and the measures we construct from it can provide.

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 within-firm differences in technology sophistication.

To study technology across firms, we start by constructing measures of the average sophistication of technology at the firm level as the simple average 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, the distribution of technology sophistication across firms, and the relationship between firm-level technology and observable characteristics.

4.1 Cross-regional differences in technology

Our exploration of technology sophistication starts by revisiting, for the three countries and 16 regions in our sample, the well-established fact that technology varies significantly across countries/regions (Comin and Hobijn, 2010; Comin and Mestieri, 2018). Table 1 presents the country-level measures of EXT constructed by averaging in each country our firm-level measures of technology sophistication. The Appendix reports the country-level values of MOST and GAP. In all cases, we observe that the ranking of countries by per-capita income levels coincides with that by average level of technology. Furthermore, cross-country differences in technology are significant. Relative to the maximum possible distance in the technology indices – the difference between the maximum level, 5, and the minimum, 1 – the difference between Brazil and Senegal in EXT is 32% for ABFs, 36% for GBFs and 29% for SSBFs. We further explore the cross-sectional relationship between average technology sophistication and development by zooming into the 16 regions that make up our sample. We construct regional measures of average technology and productivity as the weighted

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

	EXT		
	ABF	GBF	SSBF
Overall	2.58	2.67	2.30
Brazil (BR)	3.16	3.35	2.75
Vietnam (VT)	2.70	2.75	2.55
Senegal (SN)	1.87	1.92	1.59
Gap: BR - SN	1.29	1.43	1.16
Relative Gap	32%	36%	29%

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 ($(Brazil - Senegal)/MaximumGap(4)$). Technology measures are weighted by the sampling weights.

average of firm-level variables.[20] Figure 5 presents the scatter plot of the regional measures of technology sophistication (ABF MOST) against regional productivity. The correlation between these two variables is 0.93.[21]

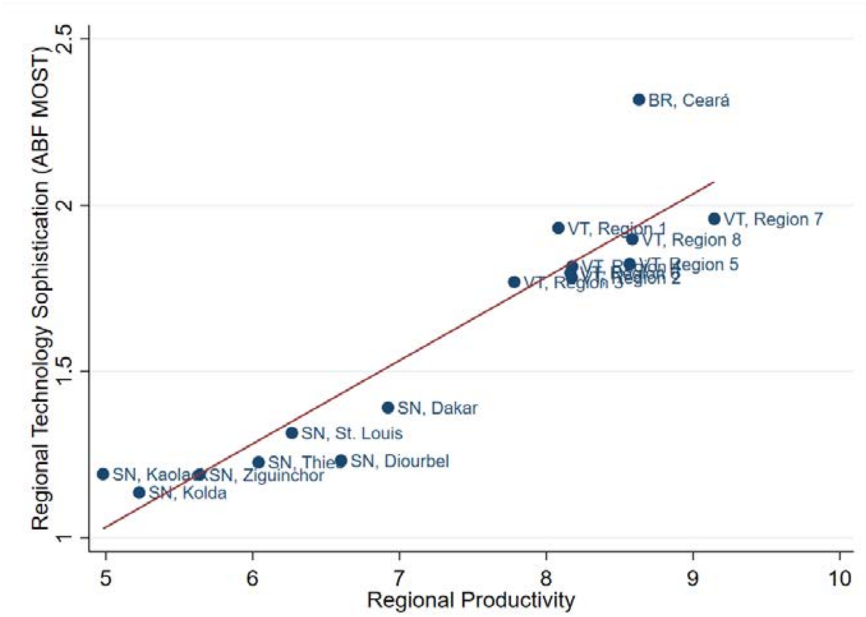


Figure 5: Region-level Technology Sophistication (MOST) vs. Regional Productivity

Note: The regional average of ABF MOST 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 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

4.2 Distribution of firm-level sophistication

Next, we turn our attention to the cross-firm distribution in technology sophistication. Figure 6 plots the kernel density of the distribution of the firm-level average value of EXT in each of the three countries. This figure illustrates that the densities of technology sophistication across firms is different in the three countries. We formally investigate this hypothesis by conducting Kolmogorov-Smirnov (KS) tests with the null that the distributions of EXT are (pairwise) equal. We reject the equivalence of all the pairwise distributions, which confirms that the distribution of EXT is different across all three countries.

[20]See the Appendix B.4 for details.

[21]The Appendix Table C.6 reports the association between regional productivity and the other measures of average technology sophistication. Figure D.1 in Appendix D presents the counterpart to Figure 5 using sophistication indices constructed with a logarithmic transformation of the technology rankings.

To better understand the differences in the distribution of technology sophistication across countries, we examine the first-order stochastic dominance of the EXT distribution across countries. We conduct the KS-based multiple test, introduced in Goldman and Kaplan (2018), which takes its null as the equivalence of all cumulative density function (CDF) values between two distributions.[22] The KS test calculates the maximum absolute difference between the two cumulative distributions with the null hypothesis that the samples are drawn from the same distribution. Instead of calculating one maximum difference, the KS-based multiple test computes all the differences between the two cumulative distributions. Appendix Figure C.1 shows the pairwise comparisons of CDFs and the results of the KS-based multiple test for each value in the variable of interest. Our tests confirm that the cross-firm distribution of EXT in Brazil first order stochastic dominates in a restricted sense[23] 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 EXT in Senegal.[24]

4.3 A within-between decomposition

Next, we explore the cross-firm dispersion in technology sophistication. Figure 6 establishes that there is significant dispersion in technology across firms, within each country. Furthermore, the cross-firm dispersion in technology sophistication seems to differ across countries.[25] We explore the magnitude of the dispersion of firm-level technology sophistication within countries by conducting a variance-covariance decomposition. Let $T_{j,c}$ denote the average technology sophistication of firm j in country c, T_c the average technology sophistication in country c, and T the average technology sophistication across all firms. Then,

$$T_{j,c} - T = \overbrace{T_{j,c} - T_c}^{Within} + \overbrace{T_c - T}^{Between} \tag{2}$$

[22] We use the STATA discomp package developed in Kaplan (2019). Because of "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. For the details of this test, please see Goldman and Kaplan (2018) and Kaplan (2019).

[23] See Atkinson (1987)

[24] Specifically for the comparison Brazil-Vietnam, we find stochastic dominance for the domain of the distribution of EXT 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 EXT [1.10, 4.70], which includes 98% of the firms in both countries' samples; and for Vietnam-Senegal the domain of EXT 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.

[25] Bloom and Van Reenen (2007) find a similarly large cross-firm dispersion in management practices.

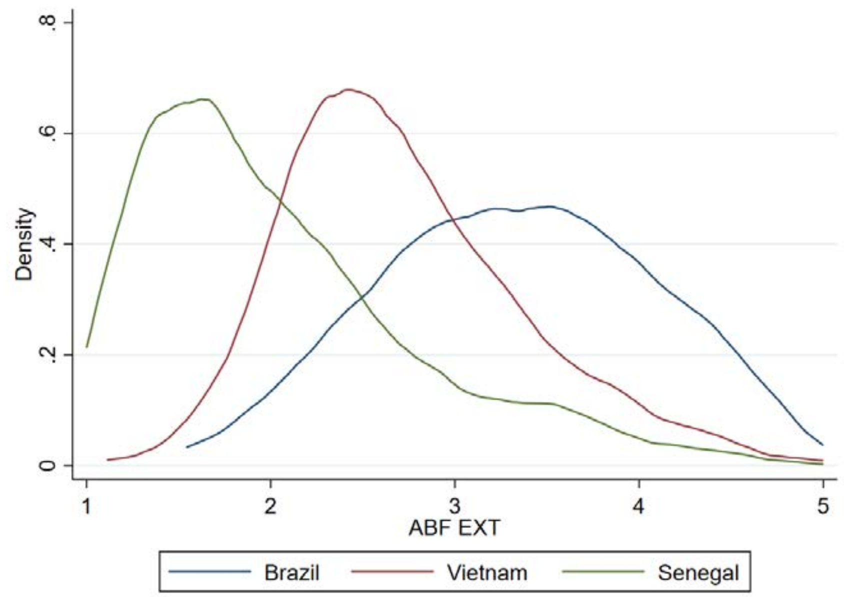


Figure 6: Distribution of Technology Sophistication (EXT)

We compute the within country component of firm variance as the ratio of the variance of the first term to the variance of the total (as, by construction, the two terms in the right-hand-side of (2) are independent). Table 2 presents the variances of the between (first row) and within (second row) terms, where the within variance is the simple average of the within variances in each of the three countries.[26] Row 6 presents the contribution of the within-country component to the total variance of the technology index.

The within-country component of cross-firm variance in technology is larger than the between-country component. For example, for MOST measures, the within component represents 55% of total for ABFs, 51% for GBFs and 83% for SSBFs. The contributions of the within component are also larger for the EXT and GAP measures. We therefore conclude that cross-firm differences in technology sophistication are larger than cross-country differences, regardless of the technology measures we consider and whether we focus on general, sector-specific or all business functions.

Figure 6 and Table 2 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 7 the cross-firm variance in each region against the regional productivity level. The figure confirms the strong association between the two variables with a correlation of 0.83.[27]

[26]Rows 3-5 report the within variance in each country.

[27]See the Appendix Table C.7 for the association with the cross-firm variance of other measures of technological sophistication. Table D.1 and Figure D.2 in Appendix D present the counterpart to Table 2

4.4 Role of observable characteristics

We next consider the contribution of other firm-level observable variables to the cross-firm variance of technology sophistication. The list of observable variables include size groups (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. We regress the firm-level average technology measure on the country dummies and the full set of dummies that capture the firm observable characteristics. The last row of Table 2 reports the within-country variance in technology across firms after controlling for the observable characteristics. The explanatory power of the controls is rather limited, and the contribution of the within-country component does not decline much after purging the variation in technology accounted for by firm controls.

Table 2: Cross-firm variance in technology sophistication

	MOST			GAP			EXT		
	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
$Var(T_c - T)$	0.17	0.24	0.06	0.02	0.01	0.05	0.28	0.34	0.26
$Var(T_{j,c} - T_c)$	0.21	0.25	0.29	0.19	0.23	0.43	0.42	0.47	0.64
$Var(T_{j,Brazil} - T_{Brazil})$	0.36	0.48	0.39	0.15	0.19	0.48	0.52	0.58	0.78
$Var(T_{j,Vietnam} - T_{Vietnam})$	0.13	0.14	0.24	0.22	0.23	0.59	0.35	0.36	0.68
$Var(T_{j,Senegal} - T_{Senegal})$	0.13	0.14	0.21	0.20	0.26	0.24	0.40	0.47	0.48
Contribution within	0.55	0.51	0.83	0.93	0.95	0.89	0.60	0.58	0.71
Contribution within with controls	0.46	0.43	0.72	0.89	0.93	0.81	0.51	0.50	0.62

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.

We conclude our analysis of cross-firm technology by exploring how the firm-level average technology sophistication varies with observable characteristics.[28] Table 3 reports the estimates of the regression of the average technology indices at the firm-level on the observables. Controlling for other observables, technology sophistication increases with firm size, but it does not vary significantly with firm age. Foreign owned firms and exporters have higher levels of technology sophistication. There is also significant variation in technology measures across sectors. For GBFs we find higher levels of both EXT and MOST in services than in manufacturing, and in manufacturing than in agriculture. For SSBFs, instead, we find that the levels of EXT and MOST are higher in agriculture.

and Figure 7 using sophistication indices constructed with a logarithmic transformation of the technology rankings.

[28]The Appendix reports the estimates for the GAP measure of technology.

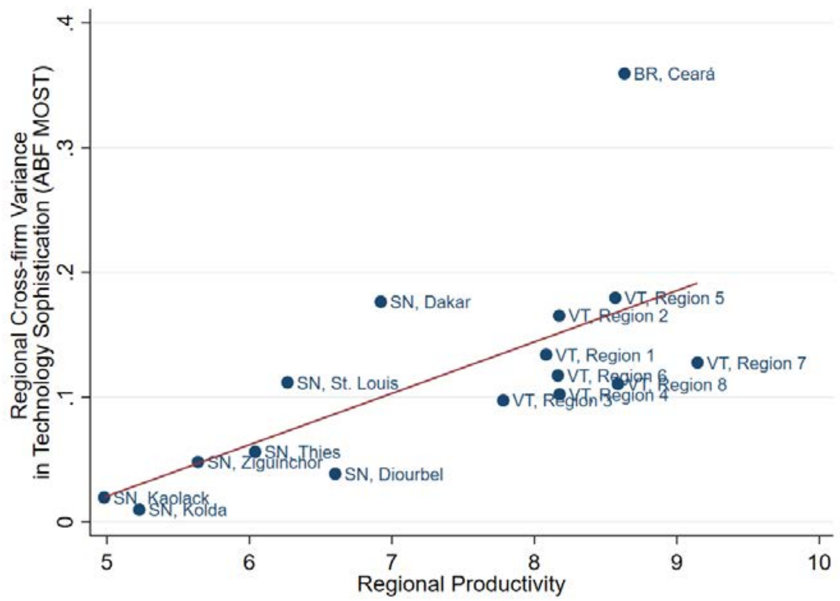


Figure 7: Cross-firm Variance of Technology Sophistication (MOST) vs. Regional Productivity

Note: The regional level cross firm variance of the ABF MOST 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 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

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. We tread into this new area by exploring three issues. In models of firm dynamics, technology is often characterized by a single firm-specific parameter. Implicit in this approach is the notion that there are good and bad firms and that good firms tend to use good technologies in all their functions and contrariwise for bad firms. The first question we investigate is whether technology sophistication is relatively uniform across the business functions of a firm or whether there is ample variation in sophistication across business functions. [29]

After quantifying the magnitude of the variation of technology sophistication within firms, we study what firm-level observable characteristics correlate with within-firm technol-

[29] Recall, that despite our use of the word firm, the fact that for multi-plant firms our data covers only one plant suggests that, it would be more appropriate to refer to observations in our dataset as plants rather than firms. Furthermore, the dispersion across business functions in technology that we study is very different in nature from cross-plant variation in technology studied in the literature (e.g., Fort, Pierce and Schott, 2018).

Table 3: Technology Sophistication and Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
		MOST			EXT	
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF
Vietnam	-0.40***	-0.55***	-0.11***	-0.46***	-0.58***	-0.20***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Senegal	-0.93***	-1.07***	-0.62***	-1.18***	-1.27***	-1.17***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Manufacturing	-0.09**	0.04	-0.36***	0.14**	0.35***	-0.31***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.07)
Services	0.05	0.30***	-0.26***	0.25***	0.63***	-0.39***
	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)
Medium	0.20***	0.22***	0.09***	0.26***	0.26***	0.24***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Large	0.53***	0.59***	0.32***	0.65***	0.63***	0.77***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.06)
Age 6 to 10	-0.02	-0.03	0.00	-0.06**	-0.04	-0.09**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Age 11 to 15	-0.01	-0.01	0.01	-0.05	-0.01	-0.10**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Age 16+	0.02	0.03	0.02	0.00	0.04	-0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Foreign Owned	0.25***	0.27***	0.22***	0.24***	0.26***	0.24***
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.07)
Exporter	0.14***	0.12***	0.10***	0.34***	0.30***	0.37***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Observations	3,896	3,896	3,076	3,893	3,889	3,080
R-squared	0.54	0.57	0.28	0.49	0.50	0.38

Note: Robust standard errors in parentheses. *** 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.

ogy sophistication. Beyond the purely descriptive relevance of this exercise, studying the correlates of within-firm volatility sheds light on the relative importance of heterogeneity in adoption costs and benefits of technology sophistication across business functions as sources of within-firm variation in technology. The third question we study is whether there are stable relationships across firms between the business function-level and the average firm-level technology sophistications. In a manner akin to Engel curves in consumption theory, such relationships can reveal insights about how business-function level technology sophistication indices aggregate into firm-level TFP.

5.1 Within-firm variance in technology

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

$$T_{f,j,c} = \alpha_j + \beta_{f,c} + u_{f,j,c}, \tag{3}$$

The business-functions dummies remove from the residual the variation generated by differences across firms in the set of relevant business functions used to calculate the technology index, such as different SSBFs. By purging this effect, the variance of the residuals, which we use to measure the within-firm dispersion in technology, are comparable across firms.[30] We consider three measures of technology sophistication: MOST, GAP and EXT. Table 4 reports the average within-firm variance in the full sample (row 1). For comparison purposes, we also report the average cross-firm variance in technology across the three countries (row 2). The main finding, and one of the most surprising in this paper, is that the within-firm variance in technology is significantly larger than the cross-firm variance in technology. The ratio of within-firm to cross-firm variances ranges from 1.9 for EXT to 3.9 for GAP.

Rows 3-5 of Table 4 report the average within-firm variance for each country. In all countries and technology measures, we confirm the regularity that the within-firm variance in technology is significantly larger than the cross-firm variance in technology. The average within-firm variance is highest in Brazil for all three measures, and it is lowest in Senegal for MOST and GAP, and in Vietnam for EXT.

Table 4: Within-firm Variance in Technology Sophistication

	ABF EXT	ABF MOST	ABF GAP
$Var(T_{f,j,c} - T_{f,c} - T_{j,c})$	0.80	0.56	0.65
$Var(T_{j,c} - T_c)$	0.42	0.20	0.17
$Var(T_{f,j,Brazil} - T_{f,Brazil} - T_{j,Brazil})$	0.97	0.93	0.75
$Var(T_{f,j,Vietnam} - T_{f,Vietnam} - T_{j,Vietnam})$	0.71	0.48	0.69
$Var(T_{f,j,Senegal} - T_{f,Senegal} - T_{j,Senegal})$	0.72	0.26	0.53
$Var(T_{j,Brazil} - T_{Brazil})$	0.52	0.36	0.15
$Var(T_{j,Vietnam} - T_{Vietnam})$	0.35	0.13	0.20
$Var(T_{j,Senegal} - T_{Senegal})$	0.40	0.12	0.16

Note: Technology measures are weighted by the sampling weights.

[30] Since our goal is to explore the dispersion in technology across business functions, we include all business functions when estimating equation (3).

We further explore the relationship between average within-firm variance and development by zooming into the regions. Figure 8 plots the average within-firm variance in each of the 16 regions against the log of regional productivity. The figure reveals a strong positive correlation between both variables (0.66).[31]

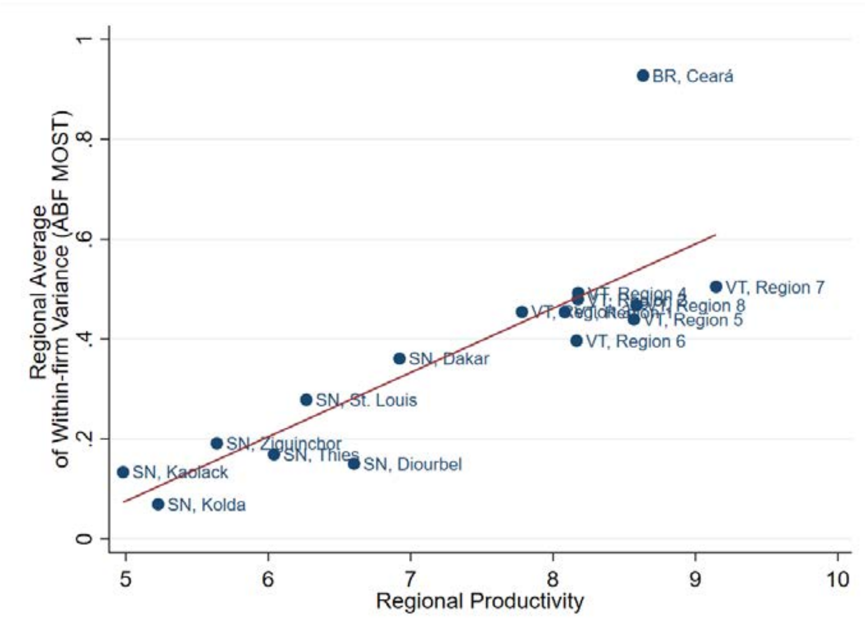


Figure 8: Within-firm Variance of Technology Sophistication (MOST) vs. Regional Productivity

Note: The regional average of within firm variance of the ABF MOST 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 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

Role of firm characteristics Next, we explore the relationship between within-firm variance, and firm characteristics such as the average level of the technology in the firm and the observable variables introduced above. Specifically, we estimate the following regression:

$$WVar_{j,c} = \alpha_c + \beta T_j + \gamma X_{j,c} + u_{j,c} \tag{4}$$

where $WVAR_{j,c}$ is the variance of technology within firm j, α_c is a country fixed effect, T_j is the average level of MOST across ABFs in firm f, and $X_{j,c}$ is a vector of firm observable

[31] In the Appendix Table C.8, we show the robustness of this finding across all measures of technology sophistication. Table D.2 and Figure D.3 in Appendix D present the counterpart to Table 4 and Figure 8 using sophistication indices constructed with a logarithmic transformation of the technology rankings.

characteristics. Table 5 reports the results.[32] For EXT and GAP, we find that within-firm variance increases with firm size, tends to be higher for firms younger than 6 years, and is higher for exporters and in services. For MOST, in contrast, these controls (other than exporter status) become insignificant once we control for the average level of technology in the firm. The most important finding in the table is that the within-firm variance in technology is strongly associated with the average level of technology across business functions. The relationship is positive and concave.

5.2 Sources of within-firm variance in technology

Before continuing with our exploration of technology use within firms, we pause and take stock of our findings so far. The magnitude of the variation in technology within the firm confirms the observation that, as we go to a more micro level, the dispersion in technology across units increases. The comparison between the dispersion in technology across countries and across firms has been suggested in the literature and we establish it with the FAT technology measures, which are more comprehensive than previous firm-level measures. To the best of our knowledge, this study is the first that documents the much greater dispersion in technology within firms than across them in a systematic manner. This finding also refutes the notion that technology is uniform within firms and poses a new question about the source of disparity in technology sophistication across business functions. In particular, does the variation in technology reflect heterogeneity across business functions in the costs of implementing more sophisticated technologies or in the benefits from having those technologies?

The estimates from Table 5 help to shed light on this question. Smaller firms are more likely to suffer from limited technical capacity and access to finance which may create differences in the use of technologies across business functions; with less sophisticated technologies being adopted in functions where firms lack expertise or where the sunk costs of adoption are larger. Conversely, since larger firms tend to face less technical difficulties and lower costs in adoption, it would be natural for adoption costs to also be less heterogeneous across business functions for large firms. However, the finding in Table 5 that the variation in technology sophistication across functions increases with firm size suggests that heterogeneity in adoption costs is probably not the main driver of within firm variance in technology.

The finding that within-firm dispersion is positively associated with the average technological sophistication of a firm is a strong indication that heterogeneity across business functions in the benefits from improving technology is a key driver of within-firm variance

[32] In the appendix we show that these findings are robust to replacing the categorical dummies for age and size by the continuous variables.

Table 5: Within-firm Variance in Technology Sophistication and Firm Characteristics

VARIABLES	(1) EXT Var(ABF)	(2) MOST Var(ABF)	(3) GAP Var(ABF)
ABF MOST	1.44***	1.49***	0.50***
	(0.09)	(0.07)	(0.11)
ABF MOST^2	-0.29***	-0.26***	-0.09***
	(0.02)	(0.02)	(0.02)
Vietnam	-0.26***	-0.35***	-0.07***
	(0.02)	(0.02)	(0.02)
Senegal	0.12***	-0.17***	-0.05*
	(0.03)	(0.02)	(0.03)
Manuf	0.24***	0.03	0.17***
	(0.04)	(0.04)	(0.04)
SVC	0.26***	0.03	0.13***
	(0.04)	(0.03)	(0.04)
Medium	0.07***	-0.02	0.01
	(0.02)	(0.02)	(0.02)
Large	0.13***	0.04	0.14***
	(0.04)	(0.03)	(0.04)
Age 6 to 10	-0.09***	0.04**	-0.08***
	(0.02)	(0.02)	(0.03)
Age 11 to 15	-0.11***	-0.01	-0.10***
	(0.02)	(0.02)	(0.03)
Age 16+	-0.10***	0.02	-0.08***
	(0.02)	(0.02)	(0.02)
MNCs	0.12***	0.03	-0.02
	(0.03)	(0.03)	(0.04)
Exporter	0.05**	0.04**	0.13***
	(0.02)	(0.02)	(0.02)
Constant	-0.92***	-1.09***	0.01
	(0.11)	(0.09)	(0.12)
Observations	3,888	3,893	3,135
R-squared	0.17	0.44	0.09

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

in technology. In particular, it is consistent with the presence of non-homotheticities in production.[33] Non-homotheticies affect the relative value of having more sophisticated technologies across business functions. As average technology in the firm increases, the value of increasing the sophistication may change at different rates across business functions. This will lead to business functions whose sophistication of technology increases more steeply with the average sophistication in the firm (i.e., technology elastic), and others where the

[33]See Hanoch (1975) and Comin, Lashkari and Mestieri (2020) for non-homotheticities in demand and Comin, Dmitriev and Rossi-Hansberg (2020) for non-homotheticities in production.

sophistication of technology increases less steeply with the average sophistication of the firm (i.e., technology-inelastic). The heterogeneity in the slopes of the expansion paths of technology (or for brevity of the technology curves) will result in greater within-firm variance in technology in firms with higher average technology.

5.3 The Technology Curve

We directly explore the relationship across firms between the sophistication of the technology used at a given business function and the overall sophistication of the firm. We refer to this relationship as the Technology Curve. We start by plotting technology curves collapsing all the firms in a decile of the distribution of average firm technology sophistication into one observation. Figure 9 plots, for each decile of the distribution of average firm sophistication (measured by the MOST ABF index), the average sophistication in the business function (vertical) against the average sophistication in the firm (horizontal axis). The top panel plots these two variables for the seven GBFs, while the other four panels focus on the SSBFs in the four sectors where we have largest firm samples (crops-agriculture, food processing, apparel, and retail and wholesale).[34] For example, the average sophistication level in "payments" for firms in the bottom decile of the distribution of average sophistication is 1.7, while their average sophistication across functions for firms in the bottom decile is 1.1.

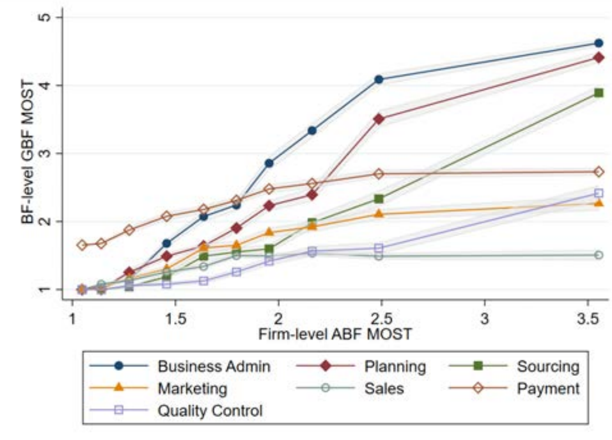
Figure 9 reveals interesting patterns. Not surprisingly, technology curves are upward sloping. That is, as we move to higher deciles in the distribution of average firm sophistication, the sophistication in any given business function tends to grow. More interestingly, the slope of the technology curves varies significantly across business functions. For example, among the GBFs, the most technology-elastic 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.

In order to investigate more systematically technology curves, we estimate the following regression:

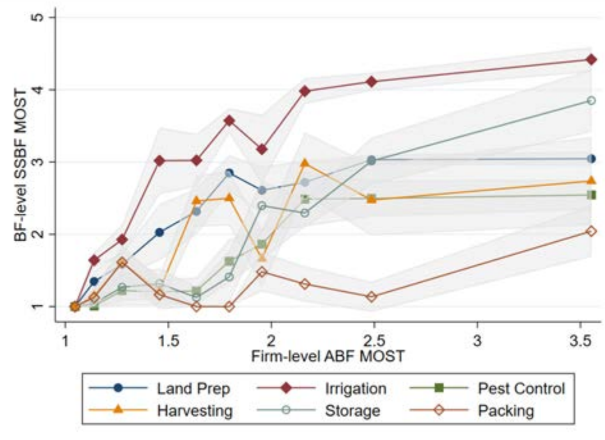
$$T_{f,j} = \alpha_f + \epsilon_f * T_j + u_{f,j} \tag{5}$$

where $T_{f,j}$ is the technology sophistication of firm j in function f, T_j is the average technology sophistication in firm j, α_f is a function-specific intercept, ϵ_f is the technology-

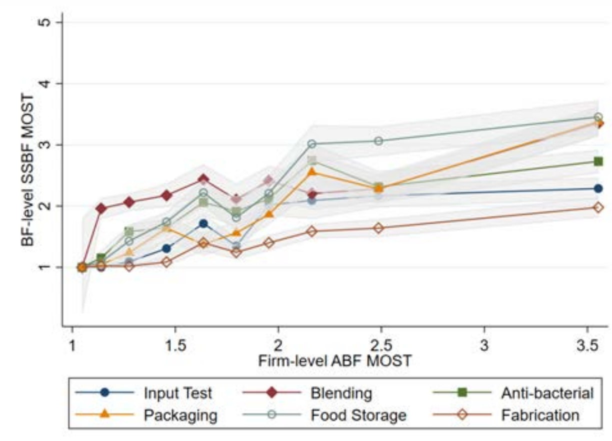
[34] These are sectors for which the survey was stratified in all countries. Additionally, we plot 95% confidence bands in the technology curves.



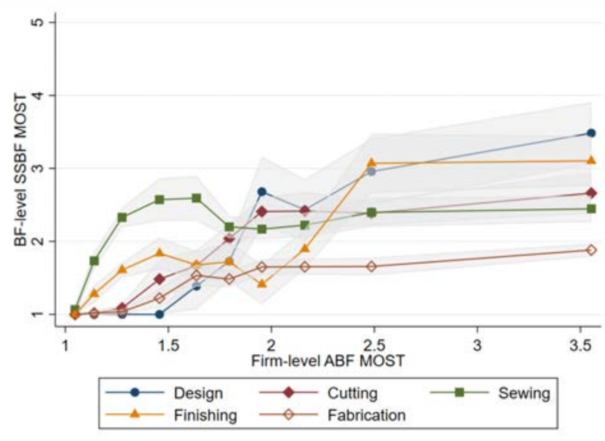
(a)



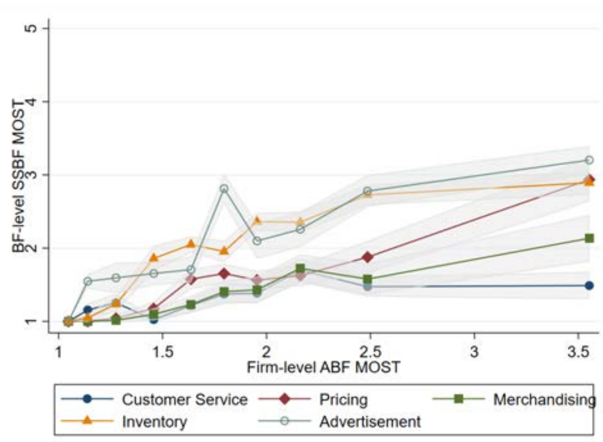
(b)



(c)



(d)



(e)

Figure 9: The Technology Curve

elasticity of business function f, and $u_{f,j}$ is an error term.

Each row of the first two columns of Table 6 reports the point estimate of ϵ_j, its standard errors, and the R^2 for one of the seven general business functions.The estimates confirm the existence of strong statistical relationship across firms between the sophistication in a given business function and the average sophistication in the firm. The point estimates of ϵ_j in all cases are positive and significant. Furthermore the explanatory power of the technology curve is surprisingly high. The R^2 of regressions (5) ranges from 12% for sales to 68% for business administration suggesting that the relation between the average sophistication in the firm and the sophistication of technology in the business function captures a large part of the cross-firm variation in the sophistication of the technologies they use at any given business function.

Table 6: Technology Curve for General Business Function

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Business Administration	1.97***	0.68	1.60***	0.21***	0.68
	(0.02)		(0.06)	(0.03)	
Production Planning	1.75***	0.62	1.79***	-0.02	0.62
	(0.02)		(0.06)	(0.03)	
Sourcing	1.33***	0.51	1.71***	-0.21***	0.52
	(0.02)		(0.05)	(0.03)	
Marketing	0.71***	0.29	0.66***	0.03	0.29
	(0.02)		(0.05)	(0.02)	
Sales	0.28***	0.12	0.13***	0.08***	0.12
	(0.01)		(0.03)	(0.02)	
Payment	0.60***	0.29	0.42***	0.10***	0.29
	(0.02)		(0.04)	(0.02)	
Quality Control	0.60***	0.23	0.58***	0.01	0.23
	(0.02)		(0.04)	(0.02)	

Note: *** p < 0.01, ** p< 0.05, * p <0.1. Dependent variables are presented in each row. In the first specification, each general business function-level technology (GBF MOST) is regressed on firm-level technology (ABF MOST). The coefficient of the ABF MOST and R-squares are presented in column (1) and (2), respectively. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. The coefficients of ABF MOST and ABF MOST*Above Median, and R-squares are presented in columns (3), (4), and (5), respectively. Robust standard errors in parentheses.

Beyond the statistical significance and explanatory power of the technology curve, Column 1 of Table 6 confirms the heterogeneity in the slopes of the technology curve across business functions. The point estimates range from almost 2 in business administration to 0.28 in sales. The ranking of business functions based on the estimated technology-elasticities is consistent with a visual inspection of Figure 9.

Appendix E investigates the technology curve for sector-specific technologies (SSBF). The estimates in Table E.1 to Table E.4 confirm both the goodness of fit as well as the heterogeneity in technology-elasticities across business functions.[35] Additionally, the Appendix extends the analysis by documenting the existence of technology curves with heterogeneous slopes across business functions when using EXT measures of technology sophistication at the business function- and firm-levels (See Table E.10 - Table E.14).

Columns 3 through 5 of Table 6 explore the linearity of technology curves, by allowing the estimate of the technology-elasticity ϵ_f to differ for companies with an average sophistication above and below the median level. In the table, we report the estimate of the coefficients for the average firm-level sophistication (column 3), and for the interaction between average sophistication and a dummy which takes the value of 1 if the firm is above the median level (column 4). The last column reports the R^2 of this regression. Our estimates reveal that in three of the seven business functions there is no statistically significant variation in the technology-elasticity above and below the median. In three others (business administration, sales and payments), there is a significantly higher technology-elasticity for firms with average sophistication above the median, and in one (sourcing) there is a lower technology-elasticity for firms with average sophistication above the median. Of the 29 functions included in our list of GBFs and SSBFs, in 15 we find a statistical different technology elasticity above than below the median level of firm-level sophistication. In eight of these 15 cases, the technology elasticity is higher above the median, while in the remaining seven it is lower.

Interestingly, even in those cases where we can statistically reject the null that the technology curve is linear, the magnitude of the changes in the technology elasticity above and below the median is relatively small. Additionally, the R^2 of equation (5) barely increases after allowing for the non-linearities in the technology curve. This finding suggests that a linear specification for the technology curve provides, to a first order, a good characterization of the patterns of technology upgrading that we observe in the data.

Robustness

In this section, we study the robustness of the characterization of the technology curves to variations in the procedure used to construct the business function-level technology sophistication indices. Specifically, we consider alternative assumptions about the mapping between the technology ranking and the indices of technology sophistication, about the nature of the most sophisticated technology in a business function and about the computation of the average sophistication in the firm.[36]

[35]These results are robust to controlling for country fixed effects (See Table E.5 - Table E.9).

[36]For brevity, we focus on the technology curves based on MOST measures of sophistication.

Table 7: Technology Curve, Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		Log		Max-1		Observed Max		Excluding BF	
General Business Function	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2
Business Administration	1.97***	0.68	1.70***	0.66	1.98***	0.68	1.92***	0.67	1.87***	0.48
	(0.02)		(0.02)		(0.02)		(0.02)		(0.03)	
Production Planning	1.75***	0.62	1.53***	0.60	1.75***	0.62	1.69***	0.61	1.59***	0.43
	(0.02)		(0.02)		(0.02)		(0.02)		(0.03)	
Sourcing	1.33***	0.51	1.26***	0.50	1.33***	0.51	1.29***	0.51	1.11***	0.34
	(0.02)		(0.02)		(0.02)		(0.02)		(0.02)	
Marketing	0.71***	0.29	0.89***	0.34	0.72***	0.29	0.69***	0.28	0.51***	0.17
	(0.02)		(0.02)		(0.02)		(0.02)		(0.02)	
Sales	0.28***	0.12	0.46***	0.19	0.26***	0.11	0.27***	0.12	0.18***	0.06
	(0.01)		(0.02)		(0.01)		(0.01)		(0.01)	
Payment	0.60***	0.29	0.57***	0.34	0.55***	0.27	0.73***	0.31	0.44***	0.18
	(0.02)		(0.01)		(0.01)		(0.02)		(0.02)	
Quality Control	0.60***	0.23	0.65***	0.24	0.70***	0.24	0.59***	0.23	0.42***	0.13
	(0.02)		(0.02)		(0.02)		(0.02)		(0.02)	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are presented in each row. In the first specification, each general business function-level technology (GBF MOST) is regressed on firm-level average technology (ABF MOST). In the second specification, we use log of ABF MOST. In the third specification, we compute ABF MOST by changing denominator from max to max-1. In the third specification, we compute ABF MOST by using observed max of technology as a denominator. In the last specification, we compute each ABF MOST by excluding a business function used in the dependent variable. Robust standard errors in parentheses.

Alternative cardinalization of sophistication index First, we explore the robustness of the technology curve to constructing business function technology indices by using a logarithmic transformation of the technology ranking. [37] Clearly, the difference with the baseline is that an increase by one step in the ranking now leads to higher increases in the sophistication index the lower the initial level of sophistication in the business function is.[38] Columns 3 and 4 of Table 7 report the slopes and fit of the technology curves estimated using the log measures of business function and average firm technology sophistication. The predictive power of the technology curve as measured by the goodness of fit is virtually unchanged; and so are the point estimates of the slopes of the technology curves. Consequently, the heterogeneity in the technology elasticities across business functions is robust to using a logarithmic mapping to construct sophistication indices.

Given how starkly different are the baseline and this alternative assumptions about scale increments, and how robust the technology curves are, we consider that the existence of stable technology curves with significant heterogeneity in slopes across business functions should be a robust finding to reasonable variations in the assumptions about scale increments used to construct technology sophistication indices at the business function level.

[37]Specifically, we assume that the new business function sophistication index is equal to the logarithm of the baseline sophistication index ($T_{f,j}^{MOST}$).

[38]Once we have computed the technology sophistication measures of business functions in this way, we compute average firm-level sophistication as the simple mean across the business functions.

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 best possible technologies across business functions. For example, in some business functions, they may consider possible technologies that are more experimental.[39] 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 function 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 technology by the highest sophistication observed in the sample for that specific business function. So what defines whether a technology is possible is the requirement that it is the most widely used technology by at least one firm in the sample.

Columns 5 through 8 of Table 7 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.

Firm-level sophistication A final concern is that the slope of the technology curve may reflect the differential effect that business functions may have on the firm-level average technology sophistication, since the business function sophistication index in the LHS is also part of the calculations of the overall index in the RHS. To explore the sensitivity of the estimates of the technology curves to the inclusion of the business function index in the overall index, we recompute the average firm-level sophistication measure in regression (5) excluding the sophistication of the business function used as dependent variable. Columns 9 and 10 of Table 7 report the estimates. Both the fit and slopes of the technology curves are robust to excluding the business function sophistication when computing the firm-level average sophistication. Therefore, the technology curve does not reflect the mechanic consequence of including the LHS variable on the RHS regressor.

Summing up, the finding that there is a technology curve that capture much of the cross-

[39] 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.

firm business function-level sophistication and that the there is great heterogeneity across business functions in the slope of technology curves is robust and significant.

6 Technology and Productivity

What is the relationship between technology measures and firm-level productivity? This question is relevant from a number of perspectives. First, showing that our measures of technology correlate with important firm-level outcomes such as labor productivity will provide an ex-post validation. Second, estimating the relationship between technology and productivity will allow us to conduct development accounting exercises and compute, for example, the dispersion in productivity across firms that can be accounted for by differences in technology across firms. Third, data limitations have led most studies to construct firm-level technology indices as simple averages of various firm-level technology measures. This practice is potentially flawed as in general the average across the function-level measures of technology is far from being a sufficient statistic of the entire distribution of technology across functions (within a firm). By exploring what moments of the distribution of technology across business functions are significantly associated with firm productivity we will gather information to construct technology indices that better reflect the actual production structure of the firm.

We study the relationship between productivity ($VAPW$)[40] and technology by estimating the following regression:

$$ln(VAPW)_{f,c} = \alpha_c + \beta_s + \gamma * T_{f,c} + \rho * X_{f,c} + v_{f,c} \tag{6}$$

where α_c and β_s are country and sector fixed effects,[41] $T_{f,c}$ is a vector of firm-level technology measures and $X_{f,c}$ a vector of controls that includes the observables discussed above plus twelve dummies for the sectors for which we have sector-specific technologies plus other services.[42] Before presenting the estimates, we stress that we interpret them as reflecting associations between various technology measures and firm productivity, and avoid making causal interpretations.

We start by exploring the conditional relationship of productivity and the mean level of technology in the firm across business functions. Column 1 of Table 8 focuses on EXT, and shows that the average technology level is significantly associated with firm productivity. Column 2 introduces a quadratic term and shows that the relationship between productivity

[40] We measure firm-level productivity as nominal value added in USD divided by the number of employees.

[41] We include one sector effect for each of the SSBFs. The left-out group is agriculture.

[42] The left-out sector is crop agriculture.

and the average level of EXT across the business functions of a firm is concave, with the maximum predicted productivity being attained when firms reach a level of EXT of 4 that corresponds to the 95^{th} percentile of the distribution of average EXT across firms. Column 3 splits EXT between MOST and GAP. We find that both are positively associated with firm-productivity and that the relationship between MOST and productivity is quadratic. In regressions not reported in the table we find that the coefficient on the quadratic term of GAP is insignificant.

Table 8: Productivity and Technology Sophistication

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)	(6) ln(VAPW)	(7) ln(VAPW)	(8) ln(VAPW)
ABF EXT	0.64***	2.51***		2.14***			2.04***	
	(0.07)	(0.33)		(0.37)			(0.36)	
ABF EXT^2		-0.32***		-0.27***			-0.22***	
		(0.06)		(0.06)			(0.06)	
ABF MOST			2.67***		2.18***	2.11***		2.27***
			(0.48)		(0.49)	(0.48)		(0.47)
ABF MOST^2			-0.45***		-0.34***	-0.33***		-0.30***
			(0.10)		(0.10)	(0.10)		(0.10)
ABF GAP			0.54***		0.45***	0.43***		0.72***
			(0.11)		(0.11)	(0.11)		(0.13)
Var(ABF EXT)				0.24**	0.34***	0.72***	1.05**	1.44***
				(0.11)	(0.10)	(0.27)	(0.42)	(0.38)
Var(ABF EXT)^2						-0.16		
						(0.10)		
Var(ABF EXT)*ABF EXT							-0.28**	-0.39***
							(0.13)	(0.12)
Firm Characteristics	√	√	√	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746	2,746	2,746	2,746
R-squared	0.49	0.50	0.49	0.50	0.50	0.50	0.50	0.50

Note: Robust standard errors in parentheses. *** 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, moto-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.

Next, we move beyond firm-level averages of technology across business functions, and explore the relationship between the within-firm variance of technology and firm productivity. Columns 4 and 5 report a positive conditional association of the within-firm variance in the EXT measure (across all business functions) and firm productivity.[43,44] Column 6 through 9 further explore the conditional relationship between firm productivity and within-firm variance. Column 6 includes the quadratic term of within-firm variance in technology and finds

[43]This finding is distinct from the positive association between within-firm variance and the average technology level, as regression (6) includes measures of the average technology (in MOST and GAP) as controls.

[44]We obtain similar findings if instead of the within-firm variance of EXT, we include the within-firm variance of MOST or GAP.

that the coefficient of this term is negative though significant only at the 10% level. Columns 7 through 8 consider the possibility that the relationship between within-firm variance in technology and productivity varies with the average level of technology in the firm. The two columns find strong evidence that the relationship between the within-firm variance in technology and productivity is less positive for firms with higher average technology levels.

Why is within-firm variance in technology positively associated with productivity, after controlling for the average technology level? One hypothesis is that, within-firm variance reflects the firm's ability to use different levels of technology across business functions. For a given average level of technology, a greater within-firm variance may lead to higher productivity if firms use better technologies in the business functions that are more relevant for the firm's operations. This strategic upgrading of technology may be particularly productive in firms that have a lower level of average technology, as it allows them to concentrate their limited capacity to implement better technologies in the key business functions. Hence, the negative coefficient of the interaction between within firm variance in technology and average firm technology in the productivity regression.

Next, we separate the average technology index in ABFs between GBFs and SSBFs to explore their relationship with firm productivity. Table 9 reports the estimated coefficients. The main take away is that both the average technology in GBFs and SSBFs matter, but that while the relationship of technology in GBFs and productivity is similar across sectors, the relationship with SSBFs differs significantly across sectors. Column 1 shows that firm productivity is positively related to the average technology in GBFs though the relationship is concave. Additionally, this specification includes the average level of SSBF in the firm. We allow the coefficient on SSBF to differ by sector to reflect both differences in the nature of sector-specific business functions as well as in the potential relevance of sector-specific technologies for productivity across sectors.[45] We find that the average level of technology in SSBFs has positive significant coefficient in agriculture, apparel, and other services, and find insignificant effects in other manufacturing and retail and wholesale. Column 2 shows the robustness of these findings to separating the average level of technology in GBFs between MOST and GAP measures, and column 3 explores the possibility that the coefficient of the average technology level in GBFs on productivity differs by broad sectors, but we do not find any statistical or economic differences.[46]

We further explore the relationship between firm-technology measures and productivity by investigating whether this relationship operates through TFP. To this end, we include as

[45]In the Appendix, we present estimates where we allow for one different coefficient for each sector (Table F.8).

[46]In the Appendix, Table F.1 shows the robustness of these findings to using MOST measures of technology in SSBF.

Table 9: Productivity and Technology Sophistication, Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
GBF EXT	1.72***		
	(0.32)		
GBF EXT^2	-0.20***		
	(0.05)		
GBF MOST		1.93***	
		(0.45)	
GBF MOST^2		-0.28***	
		(0.09)	
GBF GAP		0.38***	
		(0.10)	
GBF EXT*AGRI			0.46**
			(0.23)
GBF EXT*MANF			0.61***
			(0.08)
GBF EXT*SVC			0.49***
			(0.09)
SSBF EXT*Agriculture	0.33*	0.42**	0.43*
	(0.20)	(0.19)	(0.25)
SSBF EXT*Food Processing	0.30*	0.32*	0.28
	(0.18)	(0.18)	(0.18)
SSBF EXT*Apparel	0.44***	0.40***	0.36***
	(0.11)	(0.10)	(0.11)
SSBF EXT*Retail and Wholesale	-0.02	-0.07	-0.05
	(0.11)	(0.11)	(0.12)
SSBF EXT*Other Manufacturing	0.07	0.05	0.02
	(0.05)	(0.05)	(0.05)
SSBF EXT*Other Services	0.55**	0.58**	0.61***
	(0.23)	(0.23)	(0.23)
Var(ABF EXT)	0.29***	0.36***	0.39***
	(0.10)	(0.10)	(0.10)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.50	0.50	0.50

Note: Robust standard errors in parentheses. *** 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, moto-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.

controls in regression (6) 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 the Appendix in Table F.2 (which controls for capital per worker) and Table F.3 (which includes the controls for both capital and human capital per worker).

The main finding is that the results reported in Table 8 and 9 are robust to controlling for firm-level capital per worker and average human capital. Hence, we conclude that the strong relationship between productivity and firm technology measures in the data largely reflects the relationship between technology and firm TFP.

7 Development Accounting

We conclude our analysis by conducting two development accounting exercises. First, we study the share of the dispersion in productivity that can be accounted for by the observed dispersion in technology measures across firms. Second, we explore the possibility that differences in technology may help explain the fact that cross-country differences in productivity are much larger in agricultural than non-agricultural sectors.

7.1 Cross-firm dispersion in productivity

There is a long tradition going back at least to Mankiw, Romer and Weil (1992) studying how different factor 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 firm management practices to variation in firm productivity. We next use the productivity regressions reported in Table 8 and Table 9 to explore how much of the cross-firm dispersion in productivity firms can be accounted for the observed cross-firm variation in technological sophistication.

To answer this question, we first use the estimates of the productivity regression (6), and, for each specification, we compute the predicted values of residual productivity for all firms. These are the predicted productivity levels after filtering out the effect of observable variables other than the technology sophistication measures. Then we calculate the gap between the 10^{th} and 90^{th} percentiles of residual predicted productivity, and define this as the gap in productivity generated by differences across firms in the sophistication of technology, or for brevity the predicted productivity gap.[47]

Second, we regress firm productivity on the same observables as in regression (6). We compute the actual productivity gap as the difference in residual productivity between the productivity levels of the firms at 10^{th} and 90^{th} percentiles of distribution of residual productivity. Finally, we compare the predicted productivity gap to the actual productivity

[47]Note that we are relying on the productivity regression (6) to construct a firm-level technology index as the projection of the vector of technology measures on firm productivity. recall that the productivity regressions, include both first and second moments of the firm distribution of technology sophistication as regressors.

gap.This ratio reflects the fraction of the actual dispersion of productivity that can be accounted for by the dispersion in technology across firms. Table F.12 in the Appendix reports the predicted productivity levels at the 10^{th} and 90^{th} percentiles and the ratio of predicted over actual productivity gaps for each of the specifications we have estimated of regression 6. This ratio ranges from 31% to 37%. Therefore, we conclude that differences in firm-level measures of productivity account for one third of the gap in productivity between the firms at the 10^{th} and 90^{th} percentiles of the distribution.

7.2 Cross-country productivity gap in agriculture

One of the big puzzles in the productivity literature is the large sectoral variation we observe in cross-country productivity differences. In particular, Caselli (2005) shows that cross-country differences in productivity are ten times larger in agriculture than in non-agricultural sectors.[48] Table 10 shows that the sample of firms covered by the FAT survey also displays a larger cross-country productivity gap in agriculture than in non-agriculture. Using employment weights to compute sectoral productivity in each country, we observe that the ratio of labor productivity between Brazil and Senegal in agriculture in FAT is 15.3, while in non-agricultural sectors it is 2.5. Therefore, the relative productivity gap between the Brazilian State of Ceará and Senegal in FAT is 6.1 times greater in agriculture than in non-agricultural sectors.[49] Part of these sectoral differences in productivity reflect the larger cross-country differences in firm size in agriculture than non-agricultural sectors. As smaller production units tend to be less productive, the greater difference in average size between rich and poor countries in agriculture vs. non-agriculture explains some of the cross-sector difference in the relative productivity gap, in productivity. To filter the effect of firm-size variation we focus on raw (rather than employment weighted) firm productivity measures. The first two columns of Table 10 report the average productivity of FAT firms in each country and broad sector without using employment weights. In this case, the gap in firm productivity between Brazil and Senegal in agriculture is 11.4, while in non-agriculture is 2.9. Therefore, the ratio of the cross-country firm-productivity gaps in agriculture vs. non-agriculture is 4.

Lagakos and Waugh (2013) show that selection of labor across sectors coupled with a minimum subsistence requirement for agricultural products may generate cross-country differences in productivity that are twice larger in agriculture than in non-agricultural sectors.

[48]Unlike our data, Caselli, uses PPP adjustments to compute sectoral productivity which may induce additional discrepancies in cross-country productivity gaps across sectors if the PPP price index differs more across countries in agriculture than in non-agricultural sectors.

[49]Using World Bank Data on value added per worker by sector, the productivity ratios between these two countries in 2019 are 4.6 for agriculture and 3.1 for non-agriculture, resulting in a significantly smaller ratio than what we find in our survey (1.5 vs. 6.1).

Table 10: Average Firm Productivity

	Unweighted		Employment Weighted	
Country	AGRI	Non-AGRI	AGRI	Non-AGRI
Brazil	16,865	20,389	18,681	34,098
Vietnam	1,310	22,290	9,790	31,721
Senegal	1,476	7,062	1,222	13,697
Brazil/Senegal	11.4	2.9	15.3	2.5
Ratio: AGRI/Non-AGRI	4.0		6.1	

However, the bulk of the cross-country productivity gap in agriculture remains unexplained. A natural hypothesis that we explore next is that the cross-country gap in agricultural productivity reflects a the cross-country gap in the technologies used in production in agricultural vs. non-agricultural sectors.

Table 11: Cross-country Average Technology Sophistication by Industry

	ABF MOST			GBF MOST			SSBF MOST		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	1.93	1.75	1.89	1.76	1.76	1.97	2.17	1.60	1.68
Brazil (BR)	2.52	2.12	2.38	2.32	2.16	2.60	2.81	1.90	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	0.64	0.64
Relative Gap	32%	22%	26%	29%	23%	31%	36%	16%	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. Technology measures are weighted by the sampling weights.

Consistent with this hypothesis, Table 11 and Table C.4, in the appendix, document the existence of larger gaps in technology between Brazil and Senegal in agriculture than in non-agricultural sectors for virtually all measures we compute. To explore the potential for technology differences to account for cross-country productivity differences across sectors, we estimate the following regression.

$$ln(VAPW)_{f,c} = \alpha_c + \beta_s + \gamma_{\hat{s}} * T_{f,c} + \rho * X_{f,c} + v_{f,c} \qquad (7)$$

where we allow the coefficient of technology on productivity to differ between firms in agricultural and non-agricultural sectors (indexed by $\hat{s}$).[50]

[50] s indexes the finer sectoral disaggregation we have used in the previous section.

Table 12 reports the estimates for various specifications of regression (7). Column 1 includes as technology measures the average level of EXT at the firm level, while column 3 includes the average level of MOST. The main finding is that, for both measures, the coefficient of technology on productivity is higher for agricultural firms than for non-agricultural firms. This difference in the coefficients together with the greater cross-country gap in average technology differences in agriculture than non-agriculture firms opens the possibility for technology to account for some of the sectoral variation in the cross-country productivity gap.

Table 12: Productivity and Technology Sophistication, Industry-heterogeneity

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)	(4) ln(VAPW)	(5) ln(VAPW)
ABF EXT*AGRI	0.95***	0.84***			
	(0.20)	(0.19)			
ABF EXT*NO AGRI	0.64***	0.56***			
	(0.07)	(0.07)			
ABF MOST*AGRI			1.18***	1.07***	1.05***
			(0.30)	(0.31)	(0.36)
ABF MOST*NO AGRI			0.72***	0.67***	0.67***
			(0.10)	(0.09)	(0.09)
ABF GAP*AGRI					0.53
					(0.60)
ABF GAP*NO AGRI					0.44***
					(0.11)
Var(ABF EXT)*AGRI		0.35		0.41	0.33
		(0.30)		(0.34)	(0.30)
Var(ABF EXT)*NO AGRI		0.38***		0.51***	0.40***
		(0.10)		(0.10)	(0.10)
Firm Characteristics	√	√	√	√	√
Observations	2,746	2,746	2,746	2,746	2,746
R-squared	0.49	0.49	0.47	0.49	0.49

Note: Robust standard errors in parentheses. *** 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, moto-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.

The remaining columns in Table 12 and Table 13 explore the robustness of this key finding. Columns 2, 4 and 5 of Table 12 include as control the within-firm variance in technology. Column 5, in addition, introduces the average level of GAP in the firm. In all cases, we allow the coefficients to vary by sector. We find that the coefficient of within-firm variance in technology and average level of GAP do not differ significantly between agricultural and non-agricultural firms. Importantly, including these additional controls does not affect the difference in the coefficient of average technology on productivity between agricultural and non-agricultural firms.

Table 13: Productivity and Technology Sophistication, Industry-heterogeneity Continued

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)
GBF EXT*AGRI	0.52**	0.44**
	(0.23)	(0.22)
GBF EXT*Non-AGRI	0.54***	0.50***
	(0.07)	(0.07)
SSBF EXT*AGRI	0.46*	0.42*
	(0.25)	(0.25)
SSBF EXT*Non-AGRI	0.10*	0.04
	(0.06)	(0.06)
Var(ABF EXT)*AGRI		0.34
		(0.30)
Var(ABF EXT)*Non-AGRI		0.41***
		(0.10)
Firm Characteristics	√	√
Observations	2,746	2,746
R-squared	0.48	0.49

Note: Robust standard errors in parentheses. *** 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, moto-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.

Table 13 further explores the origin of the sectoral variation in the coefficient of average firm-level technology on productivity by separating GBFs and SSBFs. The main finding from this table is that the difference in the coefficient comes from SSBFs. Specifically, we find that the coefficients for the average technology level in GBFs is very similar for agricultural and non-agricultural firms but, while the coefficient on SSBF in the productivity of non-agricultural firms is essentially zero, the coefficient on agricultural firms is large and significant.

Next, we use the estimates from Table 12 and Table 13 to conduct a cross-sector development accounting exercise to assess the fraction of the sectoral gap in cross-country productivity difference in productivity that can be attributed to sectoral differences in technology. For each measure of technology considered in Table 12 and Table 13 we calculate the gap between Brazil and Senegal for agricultural and non-agricultural firms. Then, we use the estimated coefficients to compute the predicted average productivity gap between Brazil and Senegal in the average agricultural and non-agricultural firms. Finally, we compute the ratio of the predicted productivity gaps in agriculture vs. non-agriculture, and compare them to the actual relative cross-country productivity gap in our sample (i.e. 4.0). For example, using the specification from column 1 in Table 12, we find that the predicted productivity gap in agriculture between the average firm in Brazil and Senegal is 1.61, while in non-agriculture it is 0.99. Therefore, the ratio of the Brazil-Senegal productivity gaps in agriculture vs. non-agriculture is 1.6. This implies that differences in technology across sectors and countries account for a differential in the Brazil-Senegal productivity gap between agriculture and non-agriculture of 61% (i.e. (1.61-1)*100) which represents 21% of the actual differential in the cross-country productivity gap in our sample which is 296% (i.e. (3.96-1)*100). We conduct equivalent calculations for all the specifications of regression (7) and report them in the Appendix (Table F.13). They result in similar magnitudes with a share of the sectoral difference in Brazil-Senegal productivity gap that can be accounted for by differences in technology which ranges from 21% to 22% (see Appendix Table F.13). We conclude that about a quarter of sectoral differences in cross-country productivity can be accounted for by sectoral differences in cross-country technology.

8 Conclusions

In this paper, we have introduced the FAT dataset, a representative firm-level data set that covers Senegal, Vietnam and the Brazilian state of Ceará, and that contains comprehensive information about the technologies used in each of the key business functions of companies. Exploiting the FAT data, we have constructed measures of the sophistication of the technologies employed at the business-function and firm levels. We have then used these measures to explore the patterns of technology adoption (i) across firms, (ii) across business functions, within firms, and (iii) the relationship between technology and productivity across firms and countries.

Our exploration of the FAT dataset has revealed large cross-firm differences in the sophistication of technologies used in production. A variance-decomposition shows that the within-country component of the average firm-level sophistication of technology represents between 51% and 95% of the cross-firm variance in the average sophistication of technologies used. The cross-firm variance in technology sophistication differs across countries/regions, and is higher the more developed is the country/region in our sample.

We have conducted two development accounting exercises to conclude that variation in technology sophistication can be important to explain differences in productivity. The first has shown that cross-firm differences in technology account for a third of the gap we observe between firms at the top and bottom 10% of the productivity distribution. The second exercise has revealed that cross-country differences in the technology of the average firm in agriculture and in non-agricultural activities account for one fifth of the observed ratio between agricultural and non-agricultural cross-country firm-level productivity gaps.

The availability of comprehensive function-level information on the technologies used by companies has allowed us to systematically study technology within firms. We have documented that the variance of the within-firm component is roughly between twice and four times larger than the variance of the between company component. This finding debunks the notion implicit in the literature that "good" companies have uniformly high levels of technological sophistication across all business functions, and begs for an in depth exploration of the sources of variation in technology across business functions.

We have started to explore this question by documenting that the within-firm technology variance increases with the average technology sophistication and with firm size. These findings suggest that variation in the value of technology across business functions may be more relevant than variation in the costs of adopting the technology to explain within-firm variance. We have studied more directly this hypothesis by exploring how the sophistication of technology in a business function varies with the average sophistication of companies. We have named this relationship the technology curve. We documented that technology curves account for a large share of the cross-firm variance in business-function sophistication, and that the slope of technology curves varies greatly across business functions. The resulting patterns of technology expansion across business functions are consistent with representations of aggregate firm-level TFP that display non-homotheticities in technology sophistication.

Another surprising finding we have uncovered is that firm productivity is positively correlated with the within-firm variance in technologies after controlling for the average firm-level sophistication. The slope of this relationship is flatter for firms with higher average sophistication of technology. We have conjectured that these findings may reflect the value for firms of using more sophisticated technologies in more relevant business functions.

We hope that these findings may lay the groundwork for future empirical and theoretical efforts to better understand the drivers of technology use/adoption within firms. A significant advancement from this work may be the creation of new firm-level measures of TFP that directly reflect the technologies used and how they integrate in the firm's production structure.

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Contents (Appendix)

In the Appendix, we provide supplements to the survey, empirical exercises, and results in the main text. We begin with describing the sampling framework and weight construction for the Firm-level Adoption of Technology (FAT) Survey in Appendix A. Then, in Appendix B, we explain details on the construction of some of technology measures used in empirical exercises in the main analysis. It also provides additional figures on the structure of business functions and technologies. Finally, we provide the additional results in Appendix C, Appendix D, Appendix E, and Appendix F.

A FAT survey

The Firm-level Adoption of Technologies (FAT) data are based on multi-country, multi-sector, and representative firm surveys to measure technologies adopted and used by firms. Table A.1 provides the number of technologies covered in the FAT survey as well as other existing surveys. Compared to existing surveys, the FAT survey covers a larger number of technologies and business functions. It also covers the agriculture sector in addition to the manufacturing and service sectors.

The survey also provides balance sheet information and selected information on business owners. Furthermore, the survey collects information on potential drivers of and barriers to technology adoption. The survey has been conducted by the World Bank in partnership with public or private local agencies across three countries: Brazil (the state of Ceará), Senegal, and Vietnam. The data were collected between June 2019 and March 2020.[51]

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

A.1 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

[51]The survey is currently planned to be implemented in other countries including Bangladesh, India (the states of Tamil Nadu and Uttar Pradesh), Malawi, Kenya, the Philippines, Poland, and the Republic of Korea.

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 Labour (MTE), which covers all Brazilian formal firms. 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). The RGE covers all establishments 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, which defined the population of firms included in the FAT survey, covers firms 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 less likely to be captured in the sampling frame, due to informality, and they would require further adjustment in the survey instrument and sampling design.[52] This decision 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.[53] 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 formally registered in Ceará. Establishments with 5+ employees represent about 39% of total establishments and 93% of total employment.

[52] Establishments below this threshold often lack the organizational structure to respond to some of the questions.

[53] The ANSD uses a definition of formality based on the accounting system used by the firms. According to their definition, formal firms are those with an accounting system that is compatible with the West African Accounting System (SYSCOA). Our sample includes all firms with 5 or more employees registered under RGE, given that they tend to be also registered through the *numéro d'Identification nationale des entreprises et associations* (NINEA), which makes them more comparable with formal firms in Brazil and Vietnam.

We stratified the universe of establishments by firm size, sector of activity,and geographic regions.Our sample is representative across these dimensions.[54] 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 and 56), 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 specific for each country 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.[55] In the geographic stratification, we use sub-national regions. In Brazil, we cover only Ceará. In Vietnam, we make 8 geographic strata: Region 1 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh). In Senegal, we have 7 regional strata including Dakar, Diourbel, Kaolack, Kolda, St. Louis, Thies, and Ziguinchor. For Senegal, we additionally stratify by formality. To calculate the optimal distribution of the sample, we followed a similar methodology as described by the World Bank (2009).

For the state of Ceará, our universe includes 24,288 establishments. We collected data for 711 establishments randomly selected from RAIS. Table A.2 and Table A.3 provide the information on the distribution of firms in the population and the sample for Ceará, by size group and sectors.

Table A.2: Population Distribution, Brazil

Region	Size	Agri-culture	Food Processing	Wearing Apparel	Other Manuf.	Wholesale & Retail	Other Services	Total Region
Ceará	Small	240	523	788	2487	9255	5362	24488
	Medium	111	220	295	937	1764	1643	
	Large	47	51	54	202	243	266	
Total		398	794	1137	3626	11262	7271	24488

[54] An additional dimension was included for Senegal, splitting firms by formality status based on the ANSD definition.

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

Table A.3: 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

For Vietnam our universe includes 179,725 establishments. We collected data on 1,499 establishments randomly selected from the GSO's census. Table A.4 and Table A.5 provide the information on the distribution of firms in the population and the sample for Vietnam.

Table A.4: 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: Vietnam regions are as follows: Region 1 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

Table A.5: 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: Vietnam regions are as follows: Region 1 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

For Senegal our universe includes 9,631 establishments. We collected data for 1,786 establishments randomly selected from the RGE-ANSD. Table A.6 and Table A.7 provide the information on the distribution of firms in the population and the sample for Senegal.

Table A.6: 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

Table A.7: 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

A.2 Implementation and quality control

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. We apply the same questionnaire administered through face-to-face interviews with CAPI (computer-assisted personal interviews) in all countries. A multidisciplinary literature has emphasized that face-to-face is often more accurate than alternative modes.[56] Face-to-face mode, despite being more resource intensive, ensures more accurate responses, especially for a long questionnaire such as FAT. The average interview time can vary between 35 minutes to one hour.

We conducted a standard training in each country with enumerators, supervisors, and managers leading the data implementation. The training was led by team members directly involved on the elaboration of the questionnaire. The three days training consisted 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 included pictures of each technology mentioned in the survey both in general and sector-specific business functions, which was shared with enumerators. After going over the full questionnaire and clarifying any questions that emerged, the participants of the training went through a mock interview using Computer Assisted Personal Interviewing (CAPI), under the supervision of our team.

A pilot of the questionnaire was implemented in each country with firms out of the sample. After the pilot, our teams had the opportunity to discuss with the managers implementing the questionnaires to clarify any potential question over the implementation process. A similar check happened after 10% of data collection.

The same terms of reference to the organizations that implement the survey across all countries. These included the requirement that both the organizations, as well as the main team of interviewers, supervisors, and managers, had ample experience on collecting firm-level data in their respective country and follow similar procedures for implementing the survey.

The questionnaire was 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 was applied to the specific unit of production that was randomly selected.

The protocol for the implementation of the survey required that the survey should be

[56] 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 show also 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.

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 information about a general topic of the questionnaire, especially in modules B and C, they were requested to consult with other colleagues.

A.3 Survey Weight

We construct the sampling weight based on the inverse probability of selecting firms within each stratum. With the three stratification including industry, size, and region. The probability of selection in each country is defined as

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

where P_{isr} is the probability of selection in each strata, n_{isr} is the number of collected firms in survey, and N_{isr} is the number of firms in the universe. The base weight is defined as

$$W_{isr} = \frac{1}{P_{isr}} = \frac{N_{isr}}{n_{isr}} \tag{A.2}$$

where W_{isr} is the weight for a firm in industry i, size s, and region r.

Because of the different number of businesses in each country, a global average of three countries may be driven by one country if that country has significantly larger number of firms. To address this issue, we construct a composite weight. We first define a country probability as

$$P_c = \frac{N_c}{N} \tag{A.3}$$

where P_c is the probability of selection in each country, N_c is the number of firms in each country, and N is the total number of firms across three countries. Using both a selection probability and a country probability, we construct a composite weight as follows.

$$W_{isrc} = \frac{1}{P_{isr} * P_c} = \frac{N_{isr} * N}{n_{isr} * N_c} \tag{A.4}$$

where W_{isrc} is the composite weight for a firm in industry i, size s, region r, and country c. The composite weight and base weight produce the same statistics for each country. However, the composite weight produces global statistics by equally weighting all three countries. We use the composite weight for all the analysis in this study.

B Details on the technology measures

Appendix B describes remaining sector-specific business functions and related technologies. This section also explains the construction of technology measures in detail, which includes EXT index, aggregation of technology measures, normalization, and regional-level analysis. The FAT survey collects granular level of technology information at the business function level. In the main text, we explained how we constructed MOST, EXT, and GAP indices. In this section, we describe the technology structure and provide specific formula to construct the EXT index depending on four different types of technology structures. We also explain how we aggregate function-level technology measures at the firm-level or higher level (e.g., region-level).

B.1 Sector-specific business functions

Modules B and C of the FAT survey collect information on the technologies used in key general and sector-specific business functions. In Section 2.1, we displayed two figures (Figure 1 and Figure 2) that portray the general business functions with related technologies for each business function, and the sector specific business functions in food processing sector with related technologies.

Here, we represent the business functions and associated technologies for the remaining sectors: crops (Figure B.1), livestock (Figure B.2), wearing apparel (Figure B.3), automotive (Figure B.4), pharmaceutical (Figure B.5), wholesale and retail (Figure B.6), transportation (Figure B.7), financial services (Figure B.8), health services (Figure B.9), and other manufacturing(Figure B.10). To identify business functions and technologies, we applied the same procedures. We began with reviewing the journal articles and technical reports to understand the consensus on definition of business functions and specific technologies. Based on our research, we had several internal review process with sector specialists at the World Bank Group to specify business functions and technologies for each sector. Additionally, we engaged in an external review process with private sector experts outside of the World Bank. These experts had at least 15 years experience in a specific sector.

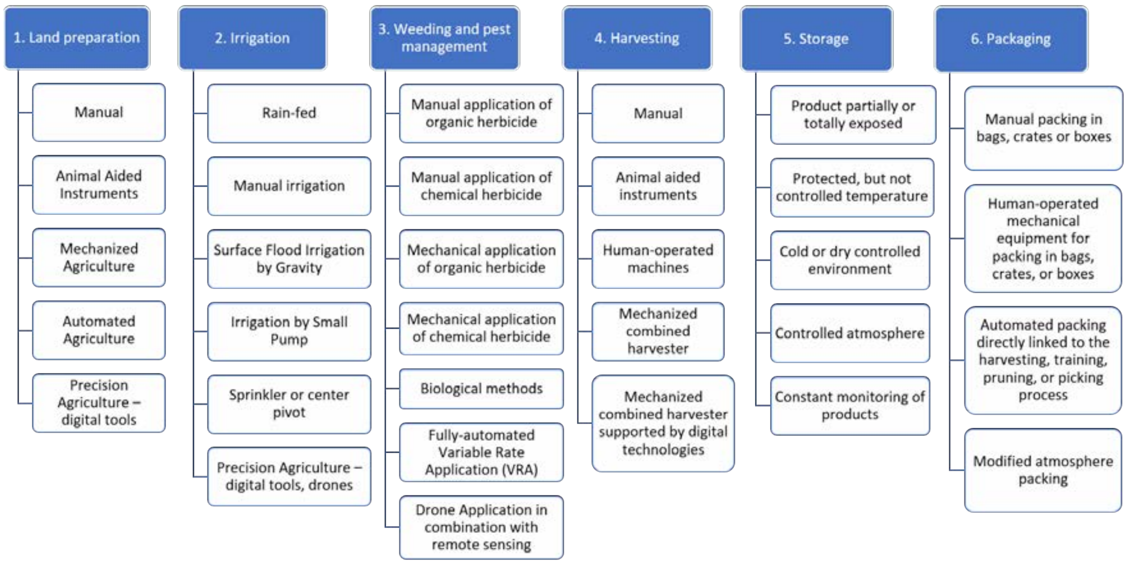

Figure B.1: Agriculture - Crops: Business Functions and Technologies

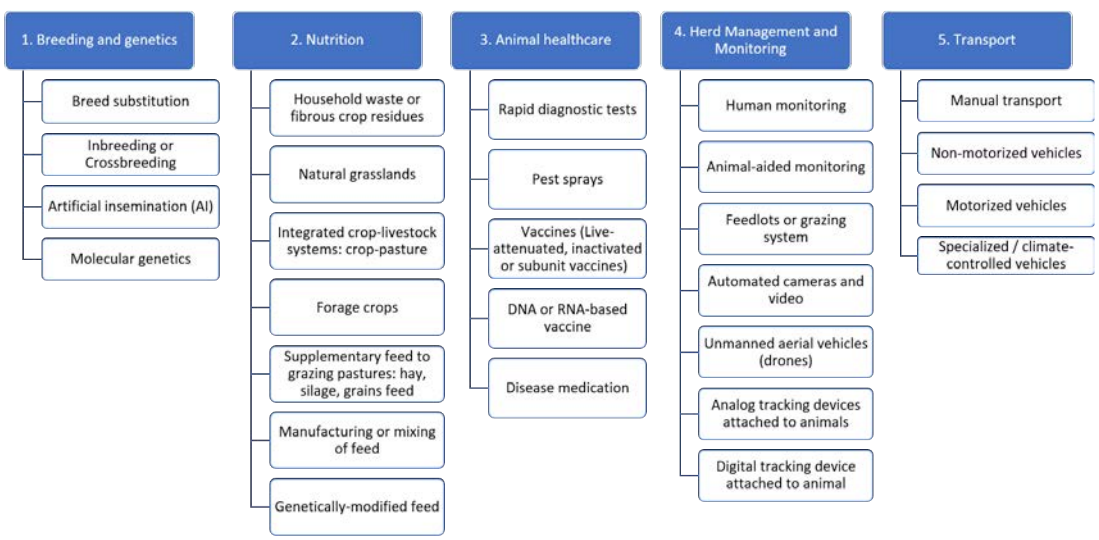

Figure B.2: Agriculture - Livestock: Business Functions and Technologies

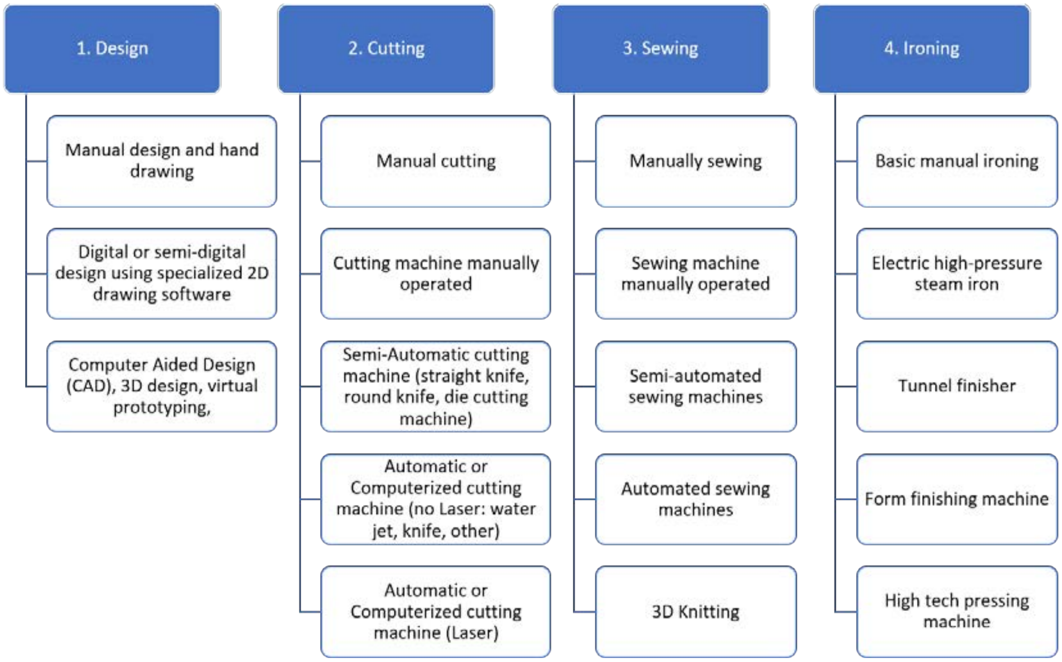

Figure B.3: Wearing Apparel: Business Functions and Technologies

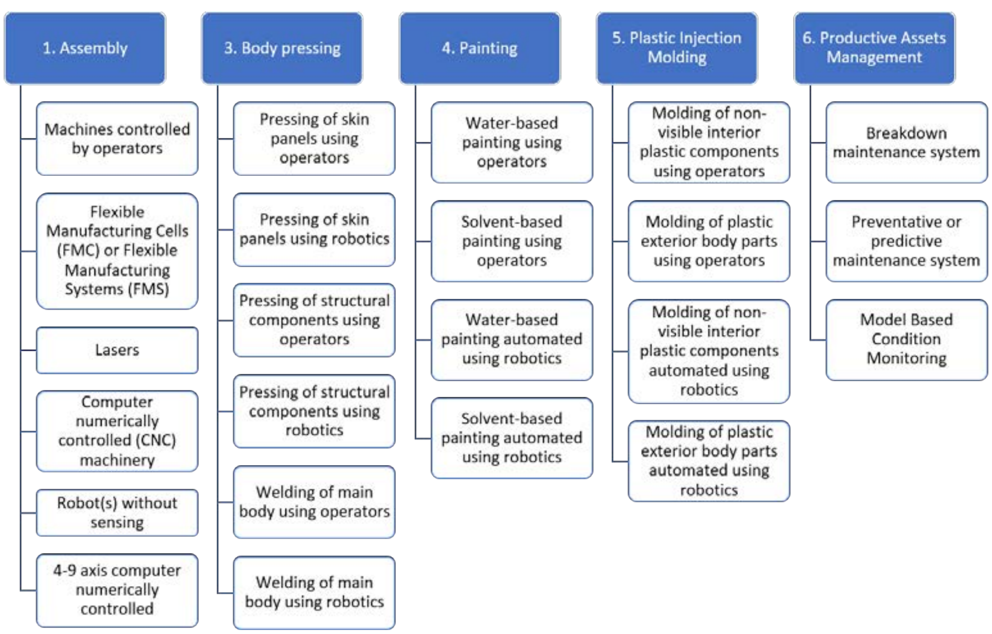

Figure B.4: Automotive: Business Functions and Technologies

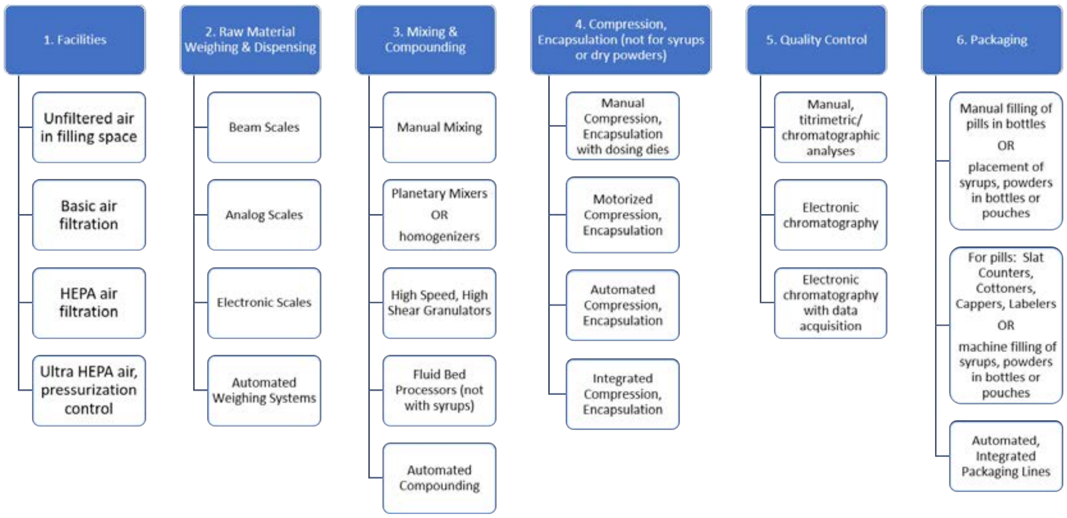

Figure B.5: Pharmaceutical: Business Functions and Technologies

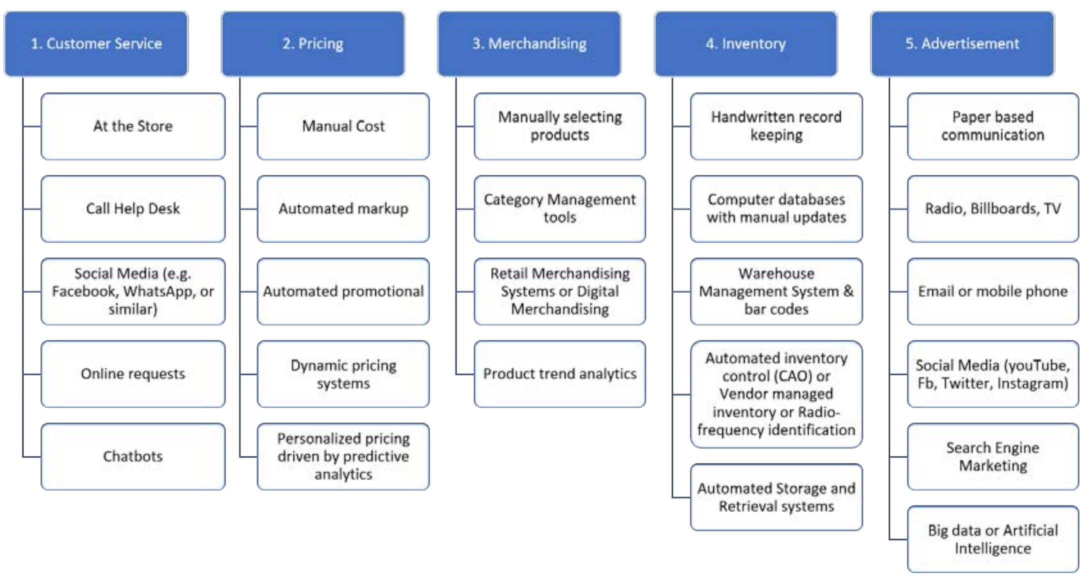

Figure B.6: Wholesale and Retail: Business Functions and Technologies

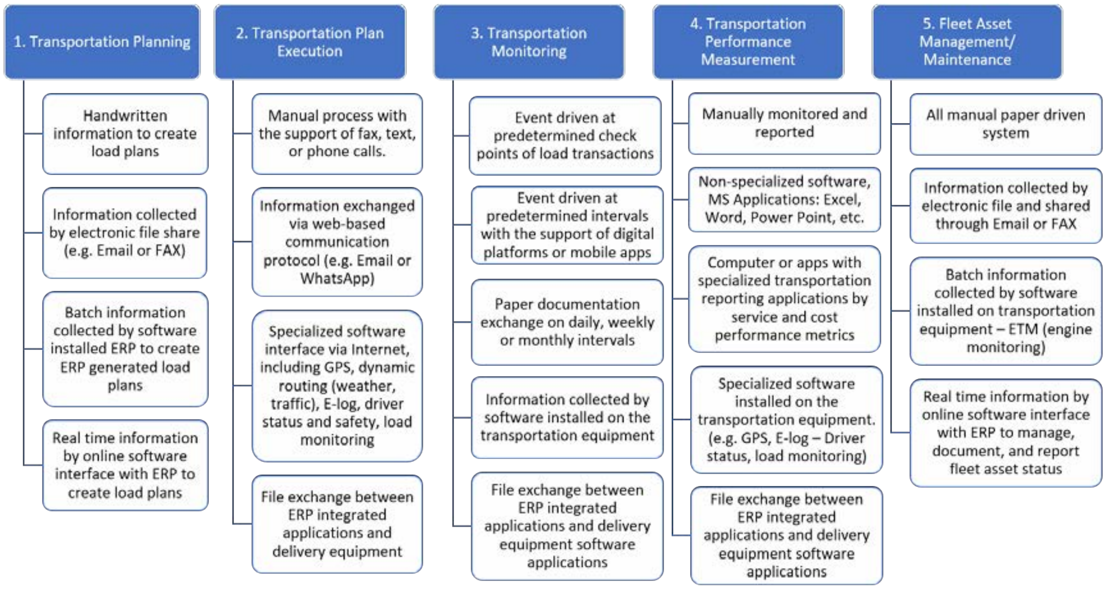

Figure B.7: Land Transportation: Business Functions and Technologies

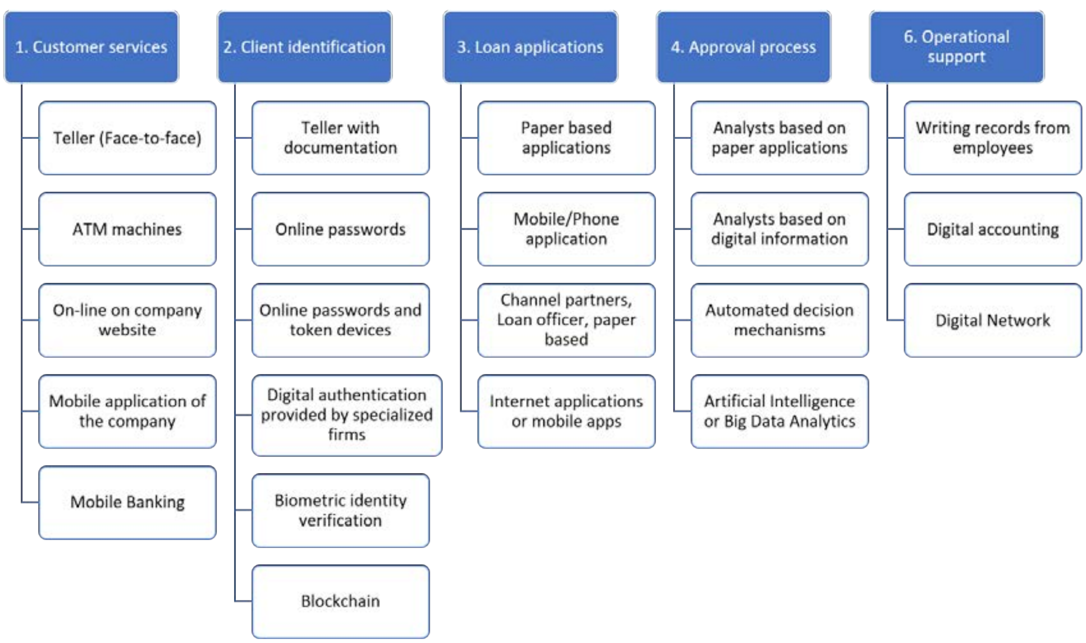

Figure B.8: Financial Services: Business Functions and Technologies

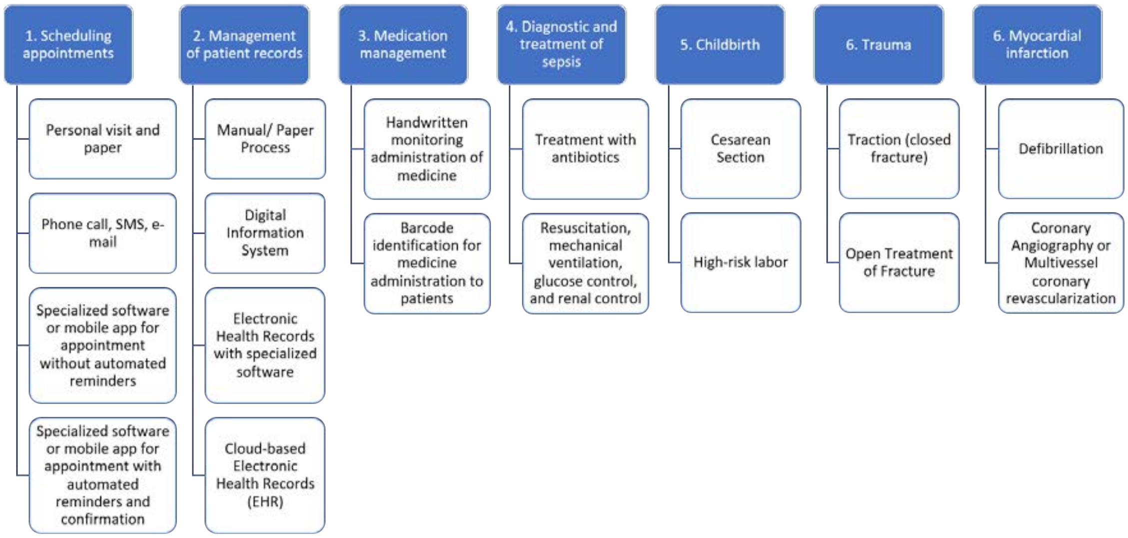

Figure B.9: Health Services: Business Functions and Technologies

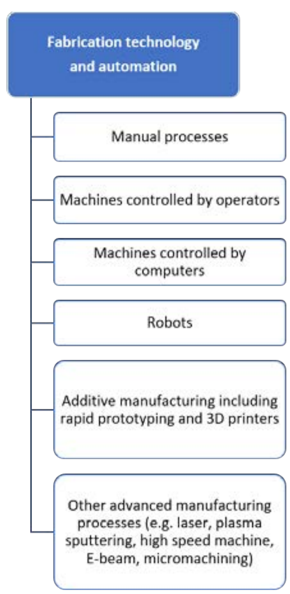

Figure B.10: Other Manufacturing: Business Functions and Technologies

B.2 Hybrid technology structures

Figure 3 illustrates various possible structures among the technologies in a business function. Different types of technology structures capture substitutability between technologies within each business function. There are four different types of technology structures defined: (1) quality ladder, (2) horizontal relationship, (3) hybrid I (i.e., two quality ladders), and (4) hybrid II (i.e., tree). In the main text, we described the structure of quality ladder (Panel A of Figure 3) as well as horizontal relationship (Panel B of Figure 3). In this section, we describe hybrid structures that combine quality ladder and horizontal relationship.

Panel C of Figure 3 represents a hybrid structure where the technologies in the function are organized in two quality ladders. In this case, the technological level of each ladder is defined by the most sophisticated technology used in the ladder, but we need to consider both ladders to define the technology level of the function. One example of this structure is the technologies used in molding of plastic injection in the automotive sector. The molding is used for both interior and exterior components of a car. The molding process can be done by operators or automated robotics. Because the molding of interior or exterior component means different process rather than different sophistication, each process has one ladder. But combined with operators or robotics, each ladder provides different sophistication of technologies.

Panel D of Figure 3 illustrates another common, hybrid structure that we refer to as a tree. Trees are characterized by a quality ladder formed by the technologies with lower sophistication and, at the top of the ladder, there is a horizontal relationship across the more sophisticated technologies that can be used in the function. An example of this structure are the technologies used in fabrication processes. Those at the bottom of the tree (manual processes and machines controlled by operators) have a clear vertical relationship. The rest of technologies in the function (machines controlled by computers, robots, additive manufacturing, and other advanced manufacturing processes), also have a vertical relationship with respect to the first two (as once present, they make irrelevant manual processes and machines controlled by operators). But, for the fours technologies with higher sophistication, it is possible to find tasks for which each of them most effective. Hence, the horizontal relationship between them. These four structures characterize all the relationships between the technologies in the functions covered in the FAT survey.[57]

In Table B.1, we provide the technology structure of each business function. We first show whether each business function is under general vs. sector specific business functions

[57] Another possible structure that we do not observe in the business functions in FAT is an inverted tree structure where at the bottom we have a horizontal relationship, and then a ladder of technologies that are technologically more sophisticated than those in the horizontal portion.

in the first column. Then, we provide the list of business functions. Finally, we specify one of four technology structures for each business function in the last column. The technology structure of each business function was, in principle, determined based on substitutability and complementarity of technologies within each business function.

Table B.1: Technology Structure of Business Function

General vs. Sectors	Business Functions	Technology Structure
General Business Function:	Administration	Quality Ladder
	Production or Service Operations Planning	Quality Ladder
	Sourcing Procurement and Supply Chain Management	Hybrid I
	Marketing and Product Development	Horizontal Relationship
	Sales	Hybrid II
	Payment Methods	Hybrid II
	Quality control	Quality Ladder
Sector Specific Business Function Agriculture Crops:	Land Preparation	Quality Ladder
	Irrigation	Quality Ladder
	Weeding and Pest Management	Quality Ladder
	Harvesting	Quality Ladder
	Storage	Quality Ladder
	Packaging	Quality Ladder
Sector Specific Business Function Agriculture Livestock:	Breeding and genetics	Quality Ladder
	Nutrition	Quality Ladder
	Anti-bacterial processes	Quality Ladder
	Herd management and monitoring	Quality Ladder
	Transport	Quality Ladder
Sector Specific Business Function Food Processing:	Input testing	Quality Ladder
	Mixing/blending/cooking	Quality Ladder
	Anti-bacterial processes	Quality Ladder
	Packaging	Quality Ladder
	Food storage	Quality Ladder
Sector Specific Business Function Wearing Apparel/Leather:	Design	Quality Ladder
	Cutting	Quality Ladder
	Sewing	Quality Ladder
	Ironing	Quality Ladder
Sector Specific Business Function Automotive:	Assembly	Horizontal Relationship
	Body Pressing	Hybrid I
	Painting	Hybrid I
	Plastic Injection Molding	Hybrid I
	Productive Asset Management	Quality Ladder
Sector Specific Business Function Pharmaceutical:	Facilities	Quality Ladder
	Raw Material Weighting and Dispensing	Quality Ladder
	Mixing and Compounding	Quality Ladder
	Compression and/or Encapsulation	Quality Ladder
	Quality Control	Quality Ladder
	Packaging	Quality Ladder
Sector Specific Business Function Wholesale and Retail:	Customer Service	Horizontal Relationship
	Pricing	Quality Ladder
	Merchandising	Quality Ladder
	Inventory	Quality Ladder
	Advertisement	Quality Ladder
Sector Specific Business Function Land Transportation:	Transportation Planning	Horizontal Relationship
	Transportation Plan Execution	Quality Ladder
	Transportation Monitoring	Quality Ladder
	Transportation Performance Measurement	Quality Ladder
	Fleet Asset Management/Maintenance	Quality Ladder
Sector Specific Business Function Financial Services:	Customer Services	Quality Ladder
	Client Identification	Quality Ladder
	Loan Applications	Quality Ladder
	Approval Process	Quality Ladder
	Operational Support	Quality Ladder
Sector Specific Business Function Health Service:	Scheduling Appointment	Horizontal Relationship
	Management of Patient Record	Quality Ladder
	Medication Management	Quality Ladder
	Diagnostic and Treatment of Sepsis	Horizontal Relationship
	Childbirth	Horizontal Relationship
	Trauma	Horizontal Relationship
	Myocardial Infarction	Horizontal Relationship
Sector Specific Business Function Other Manufacturing:	Fabrication	Hybrid II

B.3 EXT index

In the main text, we defined the MOST index as the mostly used technology, which takes a value between 1 and 5 based on the sophistication of technology. The EXT index is different from the MOST index in the following ways. First, the EXT index consider all technologies instead of the mostly used one following one of four technology structures. Below we provide equations to compute the EXT indices for each technology structure. Second, the EXT captures how much a firm explores more sophisticated technologies in each business function. For example, a firm using a standard computer software mostly for its business administration function may adopt a new specialized software or ERP system. In this case, the EXT index captures the more sophisticated technology adopted in that firm.

Let $N_{l,f}$ technologies in a given function belong to the same ladder, and let $r_{i,l,f}$ be the sophistication rank of each of the technologies. Then, we construct the EXT index for the ladder (in company c) as

$$\bar{T}_{l,f,c} = \frac{Max_i \{1_c(t_{i,l,f}) r_{i,l,f}\}}{N_{l,f}} \tag{B.1}$$

where $1_c(t_{i,l,f})$ is an indicator function that takes the value of 1 if company c uses technology t_i and 0 otherwise. In words, the EXT index in a ladder structure is the rank of the most sophisticated technology used by the company in the ladder scaled by the number of technologies in the ladder (which coincides with the maximum sophistication rank in the ladder).

Note that in functions with just one ladder (panel A of Figure 3), expression (1) gives us the EXT index for the function. If there are multiple ladders in the function (panel C of Figure 3), we construct the function level index by averaging the indices, $\bar{T}_{l,f,c}$ across ladders. That is, the function-level EXT index is

$$\bar{T}_{f,c} = \frac{\sum_l \bar{T}_{l,f,c}}{N_{l,f}} \tag{B.2}$$

where $N_{l,f}$ is the number of ladders in the function. For horizontal structures (panel B in Figure 3), the function level technology adoption index is calculated as the number of technologies used by company c in function f scaled by the total number of relevant technologies in the function. Formally, the EXT index for functions characterized by a horizontal structure is

$$\bar{T}_{f,c} = \frac{\sum_i 1_c(t_{i,f})}{N_f} \tag{B.3}$$

Finally, for tree structures (panel D in Figure 3), the EXT technology adoption index is calculated as

$$\bar{T}_{f,c} = \begin{cases} \frac{Max_i\{1_c(t_{i,f})r_{i,f}\}}{N_f} & \text{if } max_i\{1_c(t_{i,f})r_{i,f}\} \leq \bar{r}_f \\ \frac{\bar{r}_f + \sum_{i|t_i > \bar{r}_f} 1_c(t_{i,f})}{N_f} & \text{if } max_i\{1_c(t_{i,f})r_{i,f}\} > \bar{r}_f \end{cases} \tag{B.4}$$

where $\bar{r}_f$ is the rank of the last technology that conforms the pure ladder. In words, if the most sophisticated technology that the company adopts in the function is below $\bar{r}_f$, then the EXT is computed as a pure quality ladder. If the company has adopted some technology that is in the tree top (i.e. with greater sophistication than $\bar{r}_f$), then the index counts how many of those technologies the company uses, and adds them as in a horizontal relationship. We use formulas (B.1) to (B.4) to compute EXT indices at the function, company-level depending on the structure of the relationship between the technologies in each function.

All the function-company-level, the EXT indices defined so far take values in the closed interval [0,1]. This property is inherited by indices at greater levels of aggregation, since those are simple means of the function-company level indices. For some of the graphical presentations of our results, it is more appealing to re-scale the technology indices so that the lower bound is greater than zero. We therefore re-scale the technology indices in the following way

$$T^X_{j,a} = 1 + 4 * \bar{T}^X_{j,a} \tag{B.5}$$

where $\bar{T}^X_{j,a}$ is the EXT (X equal to the empty set) index for unit j at the level of aggregation a. Note that, the range of our EXT and MOST technology indices will be [1,5].

B.4 Regional-level analysis

In this section, we explain how we examine the relationship between technology and regional productivity. A cross-country analysis of the relationship between technology and productivity using FAT data would face two limitations. First, we only three countries: Brazil, Vietnam, and Senegal. In addition, the data for Brazil covers only one region, whereas the data from Vietnam and Senegal cover the entire country. To overcome these limitations, we focus on the region level to conduct aggregate cross-sectional analysis. Because all three surveys are stratified by region, regional aggregates of our technology measures are representative. Using the sampling weights, we compute the average level, cross-firm variance, and within-firm variance at the regional level for all technology measures (e.g., EXT, MOST, and GAP of ABF, GBF, and SSBF).

Another issue we must confront is that the regional-level data on GDP per capita or labor productivity is unavailable for both Senegal and Vietnam. We overcome this challenge by taking advantage of the fact that our sample of companies is representative at the regional level, and use firm-level information on value added per worker to estimate regional labor productivity from our FAT data set. Specifically, we run the following regression:

$$ln(VAPW)_{j,s,r} = \sum_r \beta_r R_r + \sum_s \beta_s S_s + \epsilon_{j,s,r} \tag{B.6}$$

where $ln(VAPW)_{j,s,r}$ is the log of value added per worker in firm j, in sector s in region r, R_r is a dummy variable for region r, and S_s 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.

Then, we further examine the relationship between technology and productivity at the regional-level. We estimate the regressions specified as follows.

$$T_r = \mu + \delta ln(VAPW)_r + \eta_r \tag{B.7}$$

where T_r is the technology for region r and $ln(VAPW)_r$ is the regional productivity.

C Additional results on cross-firm differences in technology

Appendix C provides additional results on cross-firm differences in technology. In Figure C.1, we examine the CDFs of ABF EXT across countries and provide the KS-based multiple test results on the bottom of sub-figures. The KS-based multiple test, introduced in Goldman and Kaplan (2018), takes its null as follows:

$$H_{0r} : F(k) = G(k) \tag{C.8}$$

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 technology 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 a 5% level, there is no false positives for 95% of the time. We provide the ranges of k when the null is rejected.

To provide a complete picture of our results, we provide the same results for some of omitted technology measures in the main text. Table C.1 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.

Table C.2 present the average technology for MOST and GAP measures by country as well as relative gap. In Table C.3, we provide regression results using GAP measures as dependent variable. Table C.4 shows the average technology sophistication by sector and country for EXT and GAP measures. Finally, we compute the cross-firm variance of technology sophistication by sector and country for of EXT and GAP measures in Table C.5.

For the regional analysis, we examine the relationship between technology and productivity at the regional-level. As explained above, we compute both region-level technology and productivity based on the FAT data, because the region level GDP per capita (or any other productivity measures) is not available in Senegal and Vietnam. For the region-level technology, we used three measures including the average, cross-firm variance, and average of within-firm variance of technology sophistication. Table C.6 presents the regression results of regional technology sophistication on productivity. Table C.7 shows the relationship between regional cross-firm variance and productivity. Finally, Table C.8 provides the relationship between regional average within-firm technology sophistication and regional productivity.

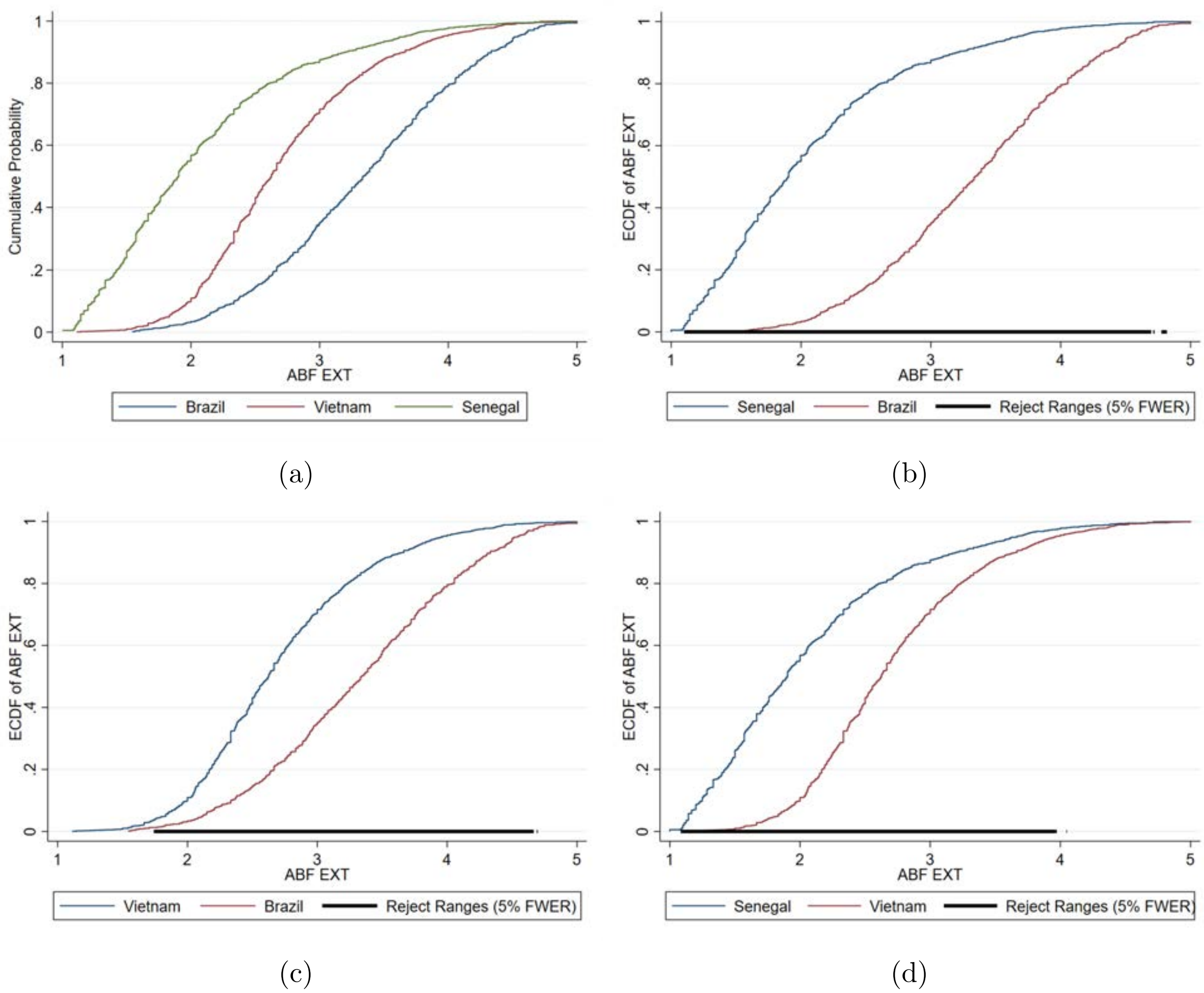

Figure C.1: CDF of Technology Sophistication with the KS-based Multiple Tests

Note: The ABF EXT 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). 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.

Table C.1: Descriptive Statistics

	(1) Overall	(2) Brazil	(3) Vietnam	(4) Senegal
Employment	39	49	46	22
S.D. of Employment	(215)	(229)	(265)	(125)
P10 of Employment	5	7	5	5
P50 of Employment	12	18	12	8
P90 of Employment	57	74	62	35
Firma Age	15	19	9	16
Export	0.124	0.041	0.169	0.162
Foreign Owned	0.059	0.008	0.120	0.048
Sectors:				
Agriculture	0.044	0.016	0.006	0.110
Food Processing	0.044	0.042	0.016	0.073
Wearing Apparel/Leather	0.084	0.051	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	0.387	0.495	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	0.175	0.138	0.207	0.179
Other Service	0.250	0.248	0.314	0.190

Note: Overall is the average of Brazil, Vietnam, and Senegal. Estimates are weighted by the sampling weights. Standard deviation of employment is reported in parenthesis.

Table C.2: Average Technology Sophistication by Country

	MOST			GAP		
	ABF	GBF	SSBF	ABF	GBF	SSBF
Overall	1.85	1.90	1.66	0.73	0.77	0.63
Brazil (BR)	2.32	2.49	1.92	0.83	0.85	0.83
Vietnam (VT)	1.91	1.92	1.80	0.80	0.84	0.74
Senegal (SN)	1.31	1.29	1.27	0.55	0.61	0.32
Gap: BR - SN	1.01	1.20	0.65	0.28	0.24	0.51
Relative Gap	25%	30%	16%	7%	6%	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 $((Brazil - Senegal)/MaximumGap(4))$. 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 C.3: Technology Sophistication and Firm Characteristics

	(1)	(2)	(3)
		GAP	
VARIABLES	ABF	GBF	SSBF
Vietnam	-0.05***	-0.03	-0.09***
	(0.02)	(0.02)	(0.03)
Senegal	-0.26***	-0.20***	-0.55***
	(0.02)	(0.02)	(0.03)
Manufacturing	0.23***	0.32***	0.05
	(0.04)	(0.04)	(0.06)
Services	0.20***	0.33***	-0.14**
	(0.04)	(0.04)	(0.06)
Medium	0.06***	0.04**	0.15***
	(0.02)	(0.02)	(0.03)
Large	0.12***	0.05	0.46***
	(0.03)	(0.03)	(0.05)
Age 6 to 10	-0.05**	-0.02	-0.09**
	(0.02)	(0.02)	(0.04)
Age 11 to 15	-0.04*	-0.00	-0.11***
	(0.02)	(0.02)	(0.04)
Age 16+	-0.02	0.00	-0.03
	(0.02)	(0.02)	(0.03)
Foreign Owned	-0.01	-0.01	0.01
	(0.03)	(0.03)	(0.06)
Exporter	0.20***	0.18***	0.27***
	(0.02)	(0.02)	(0.03)
Observations	3,893	3,888	3,076
R-squared	0.11	0.07	0.19

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

Table C.4: Average Technology Sophistication by Country and Sector

	ABF EXT			GBF EXT			SSBF EXT		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	2.51	2.51	2.63	2.37	2.54	2.76	2.71	2.40	2.24
Brazil (BR)	3.23	3.03	3.19	3.17	3.05	3.44	3.34	2.98	2.62
Vietnam (VT)	2.70	2.72	2.69	2.52	2.72	2.76	2.91	2.73	2.44
Senegal (SN)	1.59	1.78	2.02	1.41	1.86	2.09	1.87	1.48	1.66
Gap: BR - SN	1.64	1.25	1.17	1.76	1.19	1.35	1.47	1.50	0.96
Relative Gap	41%	31%	29%	44%	30%	34%	37%	38%	24%
	ABF GAP			GBF GAP			SSBF GAP		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	0.57	0.76	0.74	0.61	0.79	0.79	0.53	0.79	0.56
Brazil (BR)	0.71	0.91	0.81	0.85	0.90	0.84	0.53	1.07	0.72
Vietnam (VT)	0.68	0.87	0.77	0.73	0.84	0.83	0.58	1.09	0.54
Senegal (SN)	0.33	0.51	0.65	0.24	0.63	0.69	0.48	0.22	0.42
Gap: BR - SN	0.38	0.40	0.16	0.61	0.27	0.15	0.05	0.85	0.30
Relative Gap	10%	10%	4%	15%	7%	4%	1%	21%	8%

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 C.5: Average Within-firm Variance of Technology Sophistication by Country and Sector

	ABF MOST			GBF MOST			SSBF MOST		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	0.54	0.54	0.58	0.48	0.56	0.62	0.54	0.19	0.27
Brazil (BR)	1.00	1.01	0.90	1.03	1.08	1.00	0.83	0.31	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	0.81	0.81	0.56	0.95	0.91	0.65	0.53	0.14	0.24
Relative Gap	20%	20%	14%	24%	23%	16%	13%	4%	6%
	ABF EXT			GBF EXT			SSBF EXT		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	0.71	0.81	0.83	0.75	0.83	0.87	0.55	0.27	0.37
Brazil (BR)	0.89	1.09	0.94	1.03	1.15	1.00	0.52	0.36	0.43
Vietnam (VT)	0.76	0.69	0.72	0.75	0.66	0.72	0.72	0.13	0.40
Senegal (SN)	0.47	0.66	0.84	0.47	0.68	0.88	0.42	0.31	0.29
Gap: BR - SN	0.42	0.43	0.10	0.56	0.47	0.12	0.10	0.05	0.14
Relative Gap	11%	11%	3%	14%	12%	3%	3%	1%	4%
	ABF GAP			GBF GAP			SSBF GAP		
	AGRI	MANF	SVC	AGRI	MANF	SVC	AGRI	MANF	SVC
Overall	0.61	0.71	0.40	0.67	0.72	0.70	0.47	0.20	0.35
Brazil (BR)	0.85	0.85	0.47	0.97	0.85	0.75	0.67	0.28	0.42
Vietnam (VT)	0.60	0.72	0.39	0.64	0.70	0.70	0.44	0.11	0.37
Senegal (SN)	0.38	0.56	0.35	0.41	0.60	0.65	0.30	0.21	0.25
Gap: BR - SN	0.47	0.29	0.12	0.56	0.25	0.10	0.37	0.07	0.17
Relative Gap	12%	7%	3%	14%	6%	3%	9%	2%	4%

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 C.6: Regional Technology Sophistication and Productivity

	(1)	(2) Avg. EXT	(3)	(4)	(5) Avg. MOST	(6)	(7)	(8) Avg. GAP	(9)
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Regional Productivity	0.39***	0.41***	0.38***	0.25***	0.27***	0.21***	0.14***	0.15***	0.17***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.03)
Observations	16	16	16	16	16	16	16	16	16
R-squared	0.93	0.89	0.86	0.86	0.82	0.85	0.82	0.67	0.72

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. The observation is sub-region within each country. The firm-level average 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.

Table C.7: Regional Cross-firm Variance in Technology Sophistication and Regional Productivity

	(1)	(2) Var(EXT)	(3)	(4)	(5) Var(MOST)	(6)	(7)	(8) Var(GAP)	(9)
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Regional Productivity	0.07***	0.06**	0.02	0.13***	0.14***	0.04***	0.04***	0.07***	0.03**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	16	16	16	16	16	16	16	16	16
R-squared	0.46	0.29	0.10	0.68	0.66	0.34	0.28	0.56	0.24

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

Table C.8: Regional Average Within-Firm Variance of Technology Sophistication on Regional Productivity

	(1)	(2) Avg. of within Var(EXT)	(3)	(4)	(5) Avg. of within Var(MOST)	(6)	(7)	(8) Avg. of within Var(GAP)	(9)
VARIABLES	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
Regional Productivity	0.07***	0.06**	0.15***	0.04***	0.05**	0.05***	0.03***	0.03**	0.14***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	16	16	16	16	16	16	16	16	16
R-squared	0.51	0.39	0.72	0.44	0.37	0.60	0.49	0.28	0.71

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. The observation is sub-region within each country. The within-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.

D Robustness to using indices based on logarithmic transformations of technology sophistication rankings

In this section, we redo key parts of our analysis using alternative technology indices. These are based on business function-level sophistication indices constructed as a logarithmic function of the ordinal technology sophistication rankings. Relative to the baseline indices, the alternative indices have diminishing increments in sophistication as firms reach higher sophistication ranks in the business function.

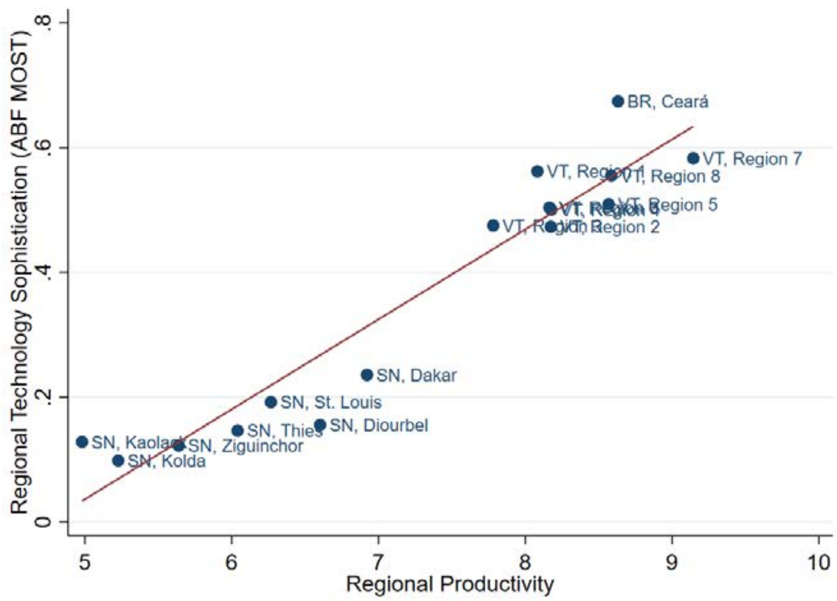

Figure D.1: Region-level Technology Sophistication (Log MOST) vs. Regional Productivity, Robustness

Note: The regional average of Log ABF MOST 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 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

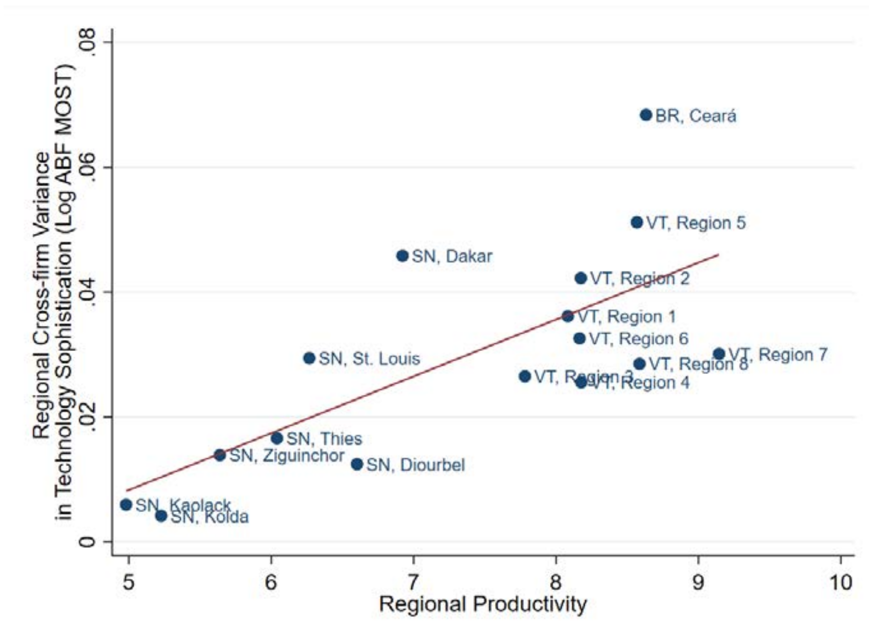

Figure D.2: Cross-firm Variance of Technology Sophistication (Log MOST) vs. Regional Productivity, Robustness

Note: The regional level cross-firm variance of the Log ABF MOST 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 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

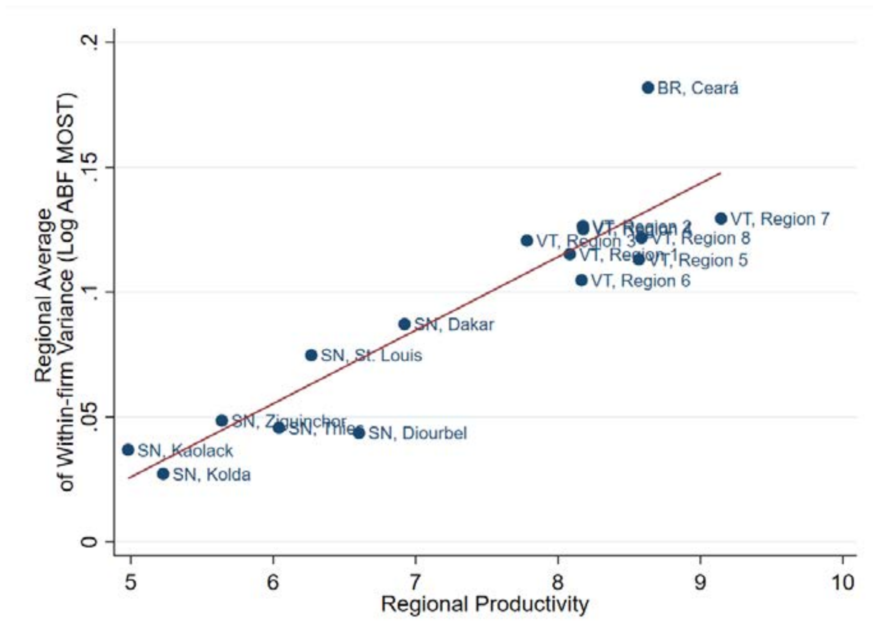

Figure D.3: Within-firm Variance of Technology Sophistication (Log MOST) vs. Regional Productivity, Robustness

Note: The regional average of within-firm variance of the Log ABF MOST 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 (Bc Ninh; Hi Phòng; Ninh Bình), Region 2 (Thái Nguyên; Bc Giang), Region 3 (Thanh Hoá; Hà Tĩnh; Bình nh), Region 4 (Kon Tum; Lâm ng), Region 5 (Bình Dng; ng Nai), Region 6 (Long An; Vĩnh Long), Region 7 (Hà Ni), and Region 8 (H Chí Minh).

Table D.1: Cross-firm Variance in Technology Sophistication, Robustness

	MOST			GAP			EXT		
	ABF	GBF	SSBF	ABF	GBF	SSBF	ABF	GBF	SSBF
$Var(T_c - T)$	0.04	0.05	0.03	0.00	0.00	0.01	0.06	0.07	0.07
$Var(T_{j,c} - T_c)$	0.04	0.05	0.07	0.03	0.04	0.08	0.07	0.08	0.12
$Var(T_{j,Brazil} - T_{Brazil})$	0.07	0.08	0.10	0.03	0.04	0.08	0.08	0.09	0.13
$Var(T_{j,Vietnam} - T_{Vietnam})$	0.03	0.04	0.07	0.03	0.04	0.10	0.05	0.05	0.11
$Var(T_{j,Senegal} - T_{Senegal})$	0.03	0.04	0.05	0.04	0.05	0.06	0.08	0.10	0.12
Contribution within	0.51	0.48	0.73	0.95	0.98	0.91	0.55	0.54	0.64
Contribution within with controls	0.49	0.52	0.27	0.05	0.02	0.09	0.45	0.46	0.36

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 D.2: Within-firm Variance in Technology Sophistication, Robustness

	ABF EXT	ABF MOST	ABF GAP
$Var(T_{f,j,c} - T_{f,c} - T_{j,c})$	0.14	0.12	0.13
$Var(T_{j,c} - T_c)$	0.07	0.04	0.03
$Var(T_{f,j,Brazil} - T_{f,Brazil} - T_{j,Brazil})$	0.16	0.18	0.15
$Var(T_{f,j,Vietnam} - T_{f,Vietnam} - T_{j,Vietnam})$	0.12	0.12	0.13
$Var(T_{f,j,Senegal} - T_{f,Senegal} - T_{j,Senegal})$	0.14	0.07	0.11
$Var(T_{j,Brazil} - T_{Brazil})$	0.08	0.07	0.03
$Var(T_{j,Vietnam} - T_{Vietnam})$	0.05	0.03	0.03
$Var(T_{j,Senegal} - T_{Senegal})$	0.08	0.03	0.03

Note: Technology measures are weighted by the sampling weights.

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

VARIABLES	(1) EXT Var(ABF)	(2) MOST Var(ABF)	(3) GAP Var(ABF)
ABF MOST	0.35***	0.50***	0.13***
	(0.02)	(0.02)	(0.02)
ABF MOST^2	-0.30***	-0.37***	-0.14***
	(0.02)	(0.01)	(0.02)
Vietnam	-0.06***	-0.07***	-0.03***
	(0.00)	(0.00)	(0.00)
Senegal	0.01***	-0.04***	-0.04***
	(0.00)	(0.00)	(0.01)
Manuf	0.03***	0.00	0.02***
	(0.01)	(0.01)	(0.01)
SVC	0.04***	0.01	0.03***
	(0.01)	(0.01)	(0.01)
Medium	0.01**	-0.00	0.00
	(0.00)	(0.00)	(0.00)
Large	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)
Age 6 to 10	-0.01***	0.01**	-0.01***
	(0.00)	(0.00)	(0.00)
Age 11 to 15	-0.01***	0.00	-0.02***
	(0.00)	(0.00)	(0.00)
Age 16+	-0.01***	0.01*	-0.01***
	(0.00)	(0.00)	(0.00)
MNCs	0.02***	0.00	-0.01
	(0.01)	(0.01)	(0.01)
Exporter	0.01**	0.01**	0.02***
	(0.00)	(0.00)	(0.00)
Constant	0.06***	0.03***	0.12***
	(0.01)	(0.01)	(0.01)
Observations	3,893	3,893	3,135
R-squared	0.14	0.38	0.08

Note: Robust standard errors in parentheses. *** 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.

Table D.4: Technology Curve Robustness for Agriculture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		Log		Max-1		Observed Max		Excluding BF	
Business Functions	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2
Land Preparation	1.29***	0.57	1.41***	0.53	1.30***	0.57	1.24***	0.56	1.16***	0.44
	(0.07)		(0.08)		(0.07)		(0.07)		(0.08)	
Irrigation	1.92***	0.70	1.65***	0.64	1.80***	0.69	1.86***	0.70	1.86***	0.56
	(0.08)		(0.08)		(0.08)		(0.08)		(0.11)	
Pest Control	0.93***	0.55	1.11***	0.59	0.94***	0.55	1.23***	0.57	0.85***	0.46
	(0.06)		(0.06)		(0.06)		(0.07)		(0.06)	
Harvesting	1.05***	0.39	1.06***	0.36	1.06***	0.39	1.01***	0.38	0.86***	0.26
	(0.09)		(0.10)		(0.09)		(0.09)		(0.10)	
Storage	1.33***	0.64	1.31***	0.62	1.35***	0.64	1.29***	0.64	1.25***	0.54
	(0.06)		(0.07)		(0.07)		(0.06)		(0.08)	
Packing	0.29***	0.09	0.35***	0.08	0.35***	0.10	0.28***	0.08	0.19**	0.04
	(0.08)		(0.10)		(0.09)		(0.08)		(0.07)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Agriculture is regressed on ABF MOST. In the second specification, we use log of ABF MOST. In the third specification, we compute ABF MOST by changing denominator from max to max-1. In the third specification, we compute ABF MOST by using observed max of technology as a denominator. In the last specification, we compute each ABF MOST by excluding a business function used in the dependent variable. Robust standard errors are provided in the parentheses.

Table D.5: Technology Curve Robustness for Food Processing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		Log		Max-1		Observed Max		Excluding BF	
Business Functions	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2
Input Test	0.76***	0.29	0.97***	0.33	0.84***	0.30	0.75***	0.29	0.61***	0.20
	(0.07)		(0.08)		(0.07)		(0.07)		(0.07)	
Mixing/Blending/Cooking	0.68***	0.12	0.66***	0.11	0.78***	0.13	0.67***	0.12	0.34***	0.03
	(0.10)		(0.10)		(0.11)		(0.10)		(0.10)	
Anti-bacterial	0.81***	0.20	0.88***	0.21	0.90***	0.21	0.81***	0.20	0.56***	0.10
	(0.10)		(0.10)		(0.11)		(0.10)		(0.10)	
Packaging	1.16***	0.36	1.19***	0.36	1.27***	0.38	1.14***	0.36	0.91***	0.22
	(0.08)		(0.08)		(0.08)		(0.08)		(0.09)	
Food Storage	1.30***	0.33	1.21***	0.32	1.44***	0.34	1.29***	0.33	0.97***	0.18
	(0.10)		(0.09)		(0.10)		(0.10)		(0.11)	
Fabrication	0.54***	0.41	0.77***	0.45	0.48***	0.41	0.53***	0.41	0.52***	0.31
	(0.03)		(0.04)		(0.03)		(0.03)		(0.02)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Food Processing is regressed on ABF MOST. In the second specification, we use log of ABF MOST. In the third specification, we compute ABF MOST by changing denominator from max to max-1. In the third specification, we compute ABF MOST by using observed max of technology as a denominator. In the last specification, we compute each ABF MOST by excluding a business function used in the dependent variable. Robust standard errors are provided in the parentheses.

Table D.6: Technology Curve Robustness for Wearing Apparel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		Log		Max-1		Observed Max		Excluding BF	
Business Functions	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2
Design	1.43***	0.51	1.38***	0.55	2.16***	0.57	0.94***	0.47	1.26***	0.37
	(0.08)		(0.07)		(0.11)		(0.06)		(0.09)	
Cutting	1.13***	0.52	1.32***	0.58	1.07***	0.52	1.16***	0.52	1.02***	0.41
	(0.05)		(0.06)		(0.05)		(0.06)		(0.06)	
Sewing	0.45***	0.08	0.50***	0.10	0.42***	0.07	0.47***	0.08	0.20**	0.02
	(0.08)		(0.08)		(0.08)		(0.08)		(0.08)	
Finishing	0.99***	0.30	0.92***	0.24	0.95***	0.29	1.00***	0.29	0.73***	0.17
	(0.08)		(0.09)		(0.08)		(0.08)		(0.09)	
Fabrication	0.55***	0.47	0.81***	0.53	0.49***	0.47	0.56***	0.47	0.52***	0.31
	(0.03)		(0.04)		(0.03)		(0.03)		(0.02)	

Note: *** p < 0.01, ** p< 0.05, * p <0.1. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Wearing Apparel is regressed on ABF MOST. In the second specification, we use log of ABF MOST. In the third specification, we compute ABF MOST by changing denominator from max to max-1. In the third specification, we compute ABF MOST by using observed max of technology as a denominator. In the last specification, we compute each ABF MOST by excluding a business function used in the dependent variable. Robust standard errors are provided in the parentheses.

Table D.7: Technology Curve Robustness for Wholesale and Retail

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		Log		Max-1		Observed Max		Excluding BF	
Business Functions	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2	ABF MOST	R^2
Customer Service	0.28***	0.06	0.50***	0.12	0.27***	0.06	0.41***	0.08	0.15***	0.02
	(0.04)		(0.06)		(0.04)		(0.06)		(0.04)	
Pricing	0.88***	0.30	0.98***	0.32	0.89***	0.30	0.86***	0.30	0.67***	0.18
	(0.06)		(0.06)		(0.06)		(0.05)		(0.06)	
Merchandising	0.64***	0.18	0.79***	0.21	0.74***	0.19	0.63***	0.18	0.43***	0.09
	(0.06)		(0.07)		(0.07)		(0.06)		(0.06)	
Inventory	1.03***	0.50	1.21***	0.58	1.03***	0.50	1.01***	0.50	0.91***	0.40
	(0.04)		(0.04)		(0.04)		(0.04)		(0.04)	
Advertisement	0.98***	0.22	1.05***	0.22	0.89***	0.21	0.97***	0.23	0.62***	0.09
	(0.10)		(0.12)		(0.10)		(0.10)		(0.11)	

Note: *** p < 0.01, ** p< 0.05, * p <0.1. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Wholesale and Retail is regressed on ABF MOST. In the second specification, we use log of ABF MOST. In the third specification, we compute ABF MOST by changing denominator from max to max-1. In the third specification, we compute ABF MOST by using observed max of technology as a denominator. In the last specification, we compute each ABF MOST by excluding a business function used in the dependent variable. Robust standard errors are provided in the parentheses.

E Additional results on within-firm technology

Appendix E presents additional results on within-firm differences in technology. In Table 6, we provides the estimates from the regression (5). In this section, we examine the robustness of the estimates and additional results on each sector specific business functions in agriculture, food processing, wearing apparel, and wholesale and retail sectors. For each business function, we estimate the following regression:

$$T_{f,j,c} = \alpha_f + \beta_c + \varepsilon_f T_j + u_{f,j,c} \tag{E.9}$$

where $T_{f,j,c}$ is the technology sophistication of firm j in function f in country c, α_f is a function-specific intercept, β_c is country fixed effects, ε_f is the technology-elasticity of business function f, T_j is the average technology sophistication in firm j, and $u_{f,j,c}$ is an error term.

To study whether the technology elasticity is constant, we introduce an interaction term between firm-level technology and an indicator that takes the value of 1 if average firm technology is above median:

$$T_{f,j,c} = \alpha_f + \beta_c + \varepsilon_{1f} T_j + \varepsilon_{2f} T_j Above_j + u_{f,j,c} \tag{E.10}$$

where Above is an indicator that firm-level technology sophistication is above the median.

We provide additional technology curve results for agriculture in Table E.1, food processing in Table E.2, wearing apparel in Table E.3, and wholesale and retail in Table E.4. Technology curves for both general and sector-specific business functions are robust to controlling for country fixed effects (see Table E.5 to Table E.9). We also estimate technology curve using EXT instead of MOST measures. Technology curves using EXT measures provide similar results for both general and sector-specific business functions (See Table E.10 to Table E.14). Finally, the results for sector-specific business functions are robust to different types of ABF MOST measures (see Table D.4 to Table D.7).

Table E.1: Technology Curve for Agriculture

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Land Preparation	1.29***	0.57	1.35***	-0.04	0.57
	(0.07)		(0.19)	(0.10)	
Irrigation	1.92***	0.70	2.07***	-0.09	0.70
	(0.08)		(0.23)	(0.12)	
Pest Control	0.93***	0.55	0.51***	0.24***	0.56
	(0.06)		(0.16)	(0.09)	
Harvesting	1.05***	0.39	1.09***	-0.02	0.39
	(0.09)		(0.27)	(0.15)	
Storage	1.33***	0.64	1.04***	0.17*	0.65
	(0.06)		(0.17)	(0.09)	
Packing	0.29***	0.09	0.93***	-0.37**	0.12
	(0.08)		(0.27)	(0.15)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Agriculture is regressed on ABF MOST. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.2: Technology Curve for Food Processing

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Input Test	0.76***	0.29	0.76***	0.00	0.29
	(0.07)		(0.16)	(0.08)	
Mixing Blending Cooking	0.68***	0.12	1.41***	-0.38***	0.15
	(0.10)		(0.24)	(0.11)	
Anti-bacterial	0.81***	0.20	0.93***	-0.06	0.20
	(0.10)		(0.24)	(0.11)	
Packaging	1.16***	0.36	1.43***	-0.14	0.37
	(0.08)		(0.20)	(0.09)	
Food Storage	1.30***	0.33	1.68***	-0.19*	0.33
	(0.10)		(0.25)	(0.12)	
Fabrication	0.54***	0.41	0.68***	-0.08**	0.42
	(0.03)		(0.08)	(0.04)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Food Processing is regressed on ABF MOST. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.3: Technology Curve for Wearing Apparel

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Design	1.43***	0.51	0.61***	0.44***	0.53
	(0.08)		(0.23)	(0.12)	
Cutting	1.13***	0.52	0.79***	0.18**	0.53
	(0.05)		(0.15)	(0.07)	
Sewing	0.45***	0.08	1.85***	-0.72***	0.20
	(0.08)		(0.20)	(0.09)	
Finishing	0.99***	0.30	1.86***	-0.46***	0.33
	(0.08)		(0.22)	(0.11)	
Fabrication	0.55***	0.47	0.52***	0.02	0.47
	(0.03)		(0.08)	(0.04)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Wearing Apparel is regressed on ABF MOST. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.4: Technology Curve for Wholesale and Retail

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Customer Service	0.28***	0.06	0.07	0.12**	0.07
	(0.04)		(0.10)	(0.05)	
Pricing	0.88***	0.30	1.25***	-0.20***	0.31
	(0.06)		(0.13)	(0.07)	
Merchandising	0.64***	0.18	0.74***	-0.05	0.18
	(0.06)		(0.15)	(0.07)	
Inventory	1.03***	0.50	1.11***	-0.04	0.51
	(0.04)		(0.09)	(0.05)	
Advertisement	0.98***	0.22	0.55**	0.24**	0.23
	(0.10)		(0.24)	(0.12)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Wholesale and Retail is regressed on ABF MOST. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.5: Technology Curve for General Business Function, Country Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Business Administration	1.81***	0.69	1.39***	0.24***	0.69
	(0.03)		(0.06)	(0.03)	
Production Planning	1.56***	0.66	1.49***	0.04	0.66
	(0.03)		(0.06)	(0.03)	
Sourcing	1.36***	0.52	1.68***	-0.18***	0.53
	(0.03)		(0.06)	(0.03)	
Marketing	0.71***	0.34	0.76***	-0.03	0.34
	(0.02)		(0.05)	(0.02)	
Sales	0.31***	0.20	0.25***	0.04**	0.21
	(0.02)		(0.03)	(0.02)	
Payment	0.48***	0.31	0.37***	0.06***	0.32
	(0.02)		(0.04)	(0.02)	
Quality Control	0.78***	0.26	0.77***	0.00	0.26
	(0.02)		(0.05)	(0.02)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each general business function-level technology (GBF MOST) is regressed on ABF MOST and country fixed effects. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.6: Technology Curve for Agriculture, Country Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Land Preparation	1.64***	0.60	1.57***	0.05	0.60
	(0.11)		(0.19)	(0.10)	
Irrigation	1.54***	0.72	1.84***	-0.19	0.72
	(0.13)		(0.23)	(0.12)	
Pest Control	0.56***	0.61	0.29*	0.17**	0.61
	(0.09)		(0.16)	(0.08)	
Harvesting	1.55***	0.46	1.34***	0.13	0.46
	(0.14)		(0.26)	(0.14)	
Storage	0.83***	0.70	0.81***	0.01	0.70
	(0.10)		(0.16)	(0.09)	
Packing	0.83***	0.21	0.98***	-0.11	0.22
	(0.13)		(0.26)	(0.16)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Agriculture is regressed on ABF MOST and country fixed effects. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.7: Technology Curve for Food Processing, Country Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Input Test	0.66***	0.30	0.68***	-0.01	0.30
	(0.08)		(0.17)	(0.08)	
Mixing Blending Cooking	1.02***	0.18	1.56***	-0.31***	0.19
	(0.12)		(0.24)	(0.12)	
Anti-bacterial	0.92***	0.24	1.25***	-0.19	0.25
	(0.12)		(0.25)	(0.12)	
Packaging	1.15***	0.36	1.47***	-0.17*	0.37
	(0.10)		(0.20)	(0.10)	
Food Storage	1.44***	0.39	1.38***	0.03	0.39
	(0.12)		(0.25)	(0.12)	
Fabrication	0.51***	0.44	0.73***	-0.12***	0.45
	(0.04)		(0.08)	(0.04)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Food Processing is regressed on ABF MOST and country fixed effects. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.8: Technology Curve for Wearing Apparel, Country Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Design	1.16***	0.52	0.61***	0.43***	0.53
	(0.15)		(0.24)	(0.14)	
Cutting	0.82***	0.54	0.72***	0.07	0.54
	(0.10)		(0.15)	(0.08)	
Sewing	1.13***	0.14	2.04***	-0.63***	0.22
	(0.14)		(0.20)	(0.10)	
Finishing	1.35***	0.34	1.77***	-0.33***	0.35
	(0.15)		(0.22)	(0.12)	
Fabrication	0.24***	0.53	0.40***	-0.11***	0.54
	(0.05)		(0.08)	(0.04)	

Note: *** $p < 0.01$, ** $p< 0.05$, * $p <0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Wearing Apparel is regressed on ABF MOST and country fixed effects. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.9: Technology Curve for Wholesale and Retail, Country Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Customer Service	0.47***	0.18	0.30***	0.09*	0.19
	(0.05)		(0.10)	(0.05)	
Pricing	1.12***	0.34	1.50***	-0.21***	0.35
	(0.07)		(0.14)	(0.06)	
Merchandising	1.00***	0.34	1.19***	-0.10	0.35
	(0.07)		(0.14)	(0.07)	
Inventory	0.91***	0.54	1.03***	-0.07	0.54
	(0.05)		(0.10)	(0.04)	
Advertisement	0.98***	0.23	0.52**	0.28**	0.25
	(0.12)		(0.24)	(0.12)	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variables are presented in each row. In the first specification, each sector specific business function-level technology (SSBF MOST) in Wholesale and Retail is regressed on ABF MOST and country fixed effects. The second specification includes an interaction term between ABF MOST and an indicator for ABF MOST above the median. Robust standard errors in parentheses.

Table E.10: Technology Curve for General Business Function

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Business Administration	1.43***	0.574	1.20***	0.12***	0.65
	(0.02)		(0.04)	(0.02)	
Production Planning	1.35***	0.63	1.20***	0.08***	0.63
	(0.02)		(0.04)	(0.02)	
Sourcing	1.08***	0.49	1.04***	0.02	0.49
	(0.02)		(0.04)	(0.02)	
Marketing	0.63***	0.36	0.73***	-0.05***	0.36
	(0.01)		(0.03)	(0.02)	
Sales	0.98***	0.42	1.01***	-0.02	0.42
	(0.02)		(0.05)	(0.02)	
Payment	0.72***	0.28	0.83***	-0.06***	0.28
	(0.02)		(0.04)	(0.02)	
Quality Control	0.90***	0.42	0.85***	0.03	0.42
	(0.02)		(0.04)	(0.02)	

Note: Dependent variables are presented in each row. In the first specification, each general business function-level technology (GBF EXT) is regressed on firm-level technology (ABF EXT). The second specification includes an interaction term between ABF EXT and an indicator for ABF EXT above the median. Robust standard errors in parentheses.

Table E.11: Technology Curve for Agriculture

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Land Preparation	0.82***	0.574	1.07***	-0.17**	0.44
	(0.06)		(0.12)	(0.07)	
Irrigation	1.35***	0.59	1.76***	-0.27***	0.60
	(0.07)		(0.16)	(0.09)	
Pest Control	0.77***	0.42	1.03***	-0.17**	0.43
	(0.06)		(0.14)	(0.08)	
Harvesting	0.99***	0.44	1.29***	-0.19*	0.45
	(0.08)		(0.19)	(0.11)	
Storage	1.16***	0.53	0.92***	0.17*	0.53
	(0.07)		(0.15)	(0.09)	
Packing	0.07	0.00	0.20	-0.08	0.01
	(0.08)		(0.23)	(0.13)	

Note: Dependent variables are presented in each row. In the first specification, each agriculture sector-specific business function-level technology (SSBF EXT) is regressed on firm-level technology (ABF EXT). The second specification includes an interaction term between ABF EXT and an indicator for ABF EXT above the median. Robust standard errors in parentheses.

Table E.12: Technology Curve for Food Processing

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Input Test	1.30***	0.574	1.01***	0.16**	0.59
	(0.06)		(0.16)	(0.08)	
Mixing Blending Cooking	0.71***	0.27	1.14***	-0.24***	0.30
	(0.06)		(0.14)	(0.07)	
Anti-bacterial	0.64***	0.26	0.70***	-0.03	0.26
	(0.06)		(0.17)	(0.09)	
Packaging	0.97***	0.38	0.67***	0.17**	0.38
	(0.06)		(0.15)	(0.07)	
Food Storage	1.01***	0.30	1.44***	-0.23**	0.31
	(0.08)		(0.20)	(0.10)	
Fabrication	0.83***	0.45	1.18***	-0.20***	0.46
	(0.05)		(0.10)	(0.05)	

Note: Dependent variables are presented in each row. In the first specification, each food processing sector-specific business function-level technology (SSBF EXT) is regressed on firm-level technology (ABF EXT). The second specification includes an interaction term between ABF EXT and an indicator for ABF EXT above the median. Robust standard errors in parentheses.

Table E.13: Technology Curve for Wearing Apparel

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Design	1.24***	0.574	0.29**	0.55***	0.64
	(0.06)		(0.14)	(0.07)	
Cutting	0.94***	0.50	0.65***	0.17***	0.51
	(0.05)		(0.11)	(0.06)	
Sewing	0.47***	0.13	0.74***	-0.15**	0.15
	(0.06)		(0.13)	(0.07)	
Finishing	0.85***	0.31	1.12***	-0.16**	0.32
	(0.07)		(0.14)	(0.08)	
Fabrication	1.06***	0.55	1.06***	-0.00	0.55
	(0.05)		(0.11)	(0.06)	

Note: Dependent variables are presented in each row. In the first specification, each wearing apparel sector-specific business function-level technology (SSBF EXT) is regressed on firm-level technology (ABF EXT). The second specification includes an interaction term between ABF EXT and an indicator for ABF EXT above the median. Robust standard errors in parentheses.

Table E.14: Technology Curve for Wholesale and Retail

	(1)	(2)	(3)	(4)	(5)
	Linear		Nonlinear		
Business Functions	ABF EXT	R-squared	ABF EXT	ABF EXT *Above Median	R-squared
Customer Service	0.99***	0.574	0.83***	0.09*	0.46
	(0.05)		(0.10)	(0.05)	
Pricing	0.95***	0.42	1.23***	-0.15***	0.43
	(0.05)		(0.10)	(0.05)	
Merchandising	0.98***	0.35	1.31***	-0.18***	0.35
	(0.06)		(0.13)	(0.06)	
Inventory	0.93***	0.50	0.98***	-0.03	0.50
	(0.04)		(0.08)	(0.04)	
Advertisement	0.97***	0.38	0.86***	0.06	0.38
	(0.07)		(0.15)	(0.07)	

Note: Dependent variables are presented in each row. In the first specification, each wholesale and retail sector-specific business function-level technology (SSBF EXT) is regressed on firm-level technology (ABF EXT). The second specification includes an interaction term between ABF EXT and an indicator for ABF EXT above the median. Robust standard errors in parentheses.

F Additional results on technology and productivity

In Appendix F, we present additional analysis on the technology and productivity. To check the robustness of the estimates in productivity regressions, we estimate several additional specifications. Table F.1 provides the additional results from the productivity regressions with separate technology indices between GBFs and SSBFs. Here, the regressions included SSBF MOST, which provide similar estimates as in the regressions with SSBF EXT.

We further examine whether our main results from the labor productivity stay with the total factor productivity (TFP) by controlling capital and human capital. We first estimate the productivity regression controlling for the book value of capital per employer as specified below.

$$ln(VAPW)_{j,c} = \alpha_c + \beta_s + \gamma T_{j,c} + \rho X_{j,c} + \theta ln(K/L)_{j,c} + v_{j,c} \tag{F.11}$$

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 Table F.2, Table F.3, and Table F.4.

We also estimate the productivity regression controlling for both capital per worker and labor cost per worker. Here, the labor cost per worker is used as a proxy for human capital. The regression is specified as:

$$ln(VAPW)_{j,c} = \alpha_c + \beta_s + \gamma T_{j,c} + \rho X_{j,c} + \theta ln(K/L)_{j,c} + \lambda ln(LC/L)_{j,c} + v_{j,c} \tag{F.12}$$

where $ln(LC/L)_{j,c}$ is the labor cost per worker. The regression results are presented in Table F.5, Table F.6, and Table F.7.

For the productivity regressions with separate technology indices between GBFs and SSBFs, we further examine whether more narrowly defined sectors provide similar results. We separate livestock from agriculture sector in Table F.8 and Table F.9. Then, we separate motor vehicle and pharmaceutical, financial services, land transportation, health services, and leather in Table F.10 and Table F.11.

We also conduct development accounting exercise in Table F.12 to examine how much dispersion in productivity across firms can be explained by differences in technology across firms. We first compute the residuals of productivity and technologies using the following specification.

$$Y_{j,c} = \alpha_c + \beta_s + \rho X_{j,c} + v_{j,c} \tag{F.13}$$

where $Y_{j,c}$ is productivity (log of value added per worker) or firm-level technology measures, α_c and β_s are country and sector fixed effects, and $X_{j,c}$ a vector of observable characteristics including size (i.e., small, medium, and large), age (i.e., 0-5, 6-10,11-15, and 16 or more), export, and multinational status.

We compute the dispersion between 10th and 90th percentiles of the residual productivity from the regression (F.13). Then, we regress the residual productivity on residual technology and compute the difference between 10th and 90th percentiles of predicted residual productivity. Finally, by dividing the dispersion in the residual productivity by the dispersion in the predicted residual productivity, we compute the percentages of the dispersion in productivity explained by the dispersion in technology.

In Table F.13, we conduct a similar development accounting exercise to understand the how much of the productivity gap between agriculture and non-agriculture sector (e.g., the ratio of 3.3 in Table 10) can be accounted for by the technology gap. From the regression (7), we compute the ratio of the predicted gap between Brazil and Senegal in agriculture to the gap in non-agriculture. Then, we compute the percentage of the actual productivity ratio between agriculture and non-agriculture explained by the predicted ratio.

Table F.1: Productivity and Technology Sophistication, GBF and SSBF MOST

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)
GBF EXT	1.72***	
	(0.32)	
GBF EXT^2	-0.20***	
	(0.05)	
GBF EXT*AGRI		1.96***
		(0.45)
GBF EXT*MANF		-0.29***
		(0.09)
GBF EXT*SVC		0.38***
		(0.10)
SSBF MOST*Agriculture	0.40**	0.48**
	(0.20)	(0.20)
SSBF MOST*Food Processing	0.36**	0.38**
	(0.19)	(0.19)
SSBF MOST*Apparel	0.65***	0.60***
	(0.15)	(0.15)
SSBF MOST*Retail and Wholesale	-0.05	-0.15
	(0.15)	(0.16)
SSBF MOST*Other Manufacturing	0.15*	0.12
	(0.09)	(0.08)
SSBF MOST*Other Services	0.49*	0.48
	(0.29)	(0.30)
Var(ABF EXT)	0.30***	0.37***
	(0.10)	(0.10)
Firm Characteristics	√	√
Observations	2,746	2,746
R-squared	0.50	0.50

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

Table F.2: 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)	(7) ln(VAPW)	(8) ln(VAPW)
ln(K/L)	0.27***	0.26***	0.26***	0.26***	0.25***	0.25***	0.26***	0.26***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
ABF EXT	0.49***	2.30***		2.02***			1.91***	
	(0.07)	(0.33)		(0.38)			(0.37)	
ABF EXT^2		-0.31***		-0.27***			-0.21***	
		(0.06)		(0.06)			(0.06)	
ABF MOST			2.34***		1.96***	1.86***		2.08***
			(0.50)		(0.51)	(0.50)		(0.49)
ABF MOST^2			-0.40***		-0.32***	-0.30***		-0.28***
			(0.10)		(0.11)	(0.10)		(0.10)
ABF GAP			0.41***		0.32***	0.29**		0.61***
			(0.11)		(0.11)	(0.12)		(0.13)
Var(ABF EXT)				0.19*	0.29***	0.91***	1.07**	1.54***
				(0.10)	(0.10)	(0.27)	(0.45)	(0.41)
Var(ABF EXT)^2						-0.26***		
						(0.09)		
Var(ABF EXT)*ABF EXT							-0.30**	-0.43***
							(0.14)	(0.13)
Firm Characteristics	√	√	√	√	√	√	√	√
Observations	2,519	2,519	2,519	2,519	2,519	2,519	2,519	2,519
R-squared	0.53	0.55	0.54	0.55	0.54	0.55	0.55	0.55

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

Table F.3: Productivity and Technology Sophistication Controlling for ln(K/L), GBF and SSBF EXT

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
ln(K/L)	0.26***	0.26***	0.26***
	(0.04)	(0.04)	(0.04)
GBF EXT	1.66***		
	(0.32)		
GBF EXT^2	-0.21***		
	(0.05)		
GBF MOST		1.81***	
		(0.49)	
GBF MOST^2		-0.28***	
		(0.10)	
GBF GAP		0.31***	
		(0.10)	
GBF EXT*AGRI			0.25
			(0.24)
GBF EXT*MANF			0.54***
			(0.07)
GBF EXT*SVC			0.38***
			(0.08)
SSBF EXT*Agriculture	-0.02	0.06	0.18
	(0.27)	(0.26)	(0.33)
SSBF EXT*Food Processing	0.15	0.17	0.11
	(0.18)	(0.18)	(0.18)
SSBF EXT*Apparel	0.34***	0.30***	0.24**
	(0.11)	(0.10)	(0.11)
SSBF EXT*Retail and Wholesale	-0.04	-0.08	-0.06
	(0.11)	(0.11)	(0.12)
SSBF EXT*Other Manufacturing	0.04	0.02	-0.02
	(0.05)	(0.05)	(0.05)
SSBF EXT*Other Services	0.39*	0.44**	0.46**
	(0.21)	(0.20)	(0.21)
Var(ABF EXT)	0.22**	0.30***	0.33***
	(0.10)	(0.10)	(0.10)
Firm Characteristics	√	√	√
Observations	2,519	2,519	2,519
R-squared	0.55	0.55	0.54

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

Table F.4: Productivity and Technology Sophistication Controlling for ln(K/L), GBF and SSBF MOST

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)
ln(K/L)	0.26***	0.26***
	(0.04)	(0.04)
GBF EXT	1.67***	
	(0.32)	
GBF EXT^2	-0.21***	
	(0.05)	
GBF EXT*AGRI		1.84***
		(0.50)
GBF EXT*MANF		-0.29***
		(0.10)
GBF EXT*SVC		0.30***
		(0.10)
SSBF MOST*Agriculture	0.08	0.15
	(0.25)	(0.25)
SSBF MOST*Food Processing	0.28	0.29
	(0.18)	(0.18)
SSBF MOST*Apparel	0.51***	0.46***
	(0.15)	(0.14)
SSBF MOST*Retail and Wholesale	-0.03	-0.13
	(0.14)	(0.14)
SSBF MOST*Other Manufacturing	0.15*	0.12*
	(0.08)	(0.07)
SSBF MOST*Other Services	0.18	0.19
	(0.25)	(0.26)
Var(ABF EXT)	0.22**	0.30***
	(0.10)	(0.10)
Firm Characteristics	√	√
Observations	2,519	2,519
R-squared	0.55	0.55

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

Table F.5: 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)	(7) ln(VAPW)	(8) ln(VAPW)
ln(K/L)	0.14***	0.14***	0.14***	0.14***	0.13***	0.13***	0.14***	0.14***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ln(Labor Cost/L)	0.68***	0.66***	0.67***	0.67***	0.67***	0.67***	0.67***	0.67***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
ABF EXT	0.28***	1.27***		0.87**			0.79**	
	(0.07)	(0.31)		(0.35)			(0.35)	
ABF EXT^2		-0.17***		-0.11**			-0.06	
		(0.05)		(0.05)			(0.06)	
ABF MOST			1.61***		1.25**	1.14**		1.34***
			(0.48)		(0.49)	(0.48)		(0.48)
ABF MOST^2			-0.30***		-0.22**	-0.20**		-0.19**
			(0.10)		(0.10)	(0.10)		(0.10)
ABF GAP			0.27***		0.19*	0.16		0.38***
			(0.10)		(0.11)	(0.11)		(0.13)
Var(ABF EXT)				0.26***	0.28***	0.92***	1.02**	1.10***
				(0.10)	(0.10)	(0.25)	(0.45)	(0.42)
Var(ABF EXT)ˆ2						-0.26***		
						(0.08)		
Var(ABF EXT)*ABF EXT							-0.26*	-0.28**
							(0.14)	(0.13)
Firm Characteristics	√	√	√	√	√	√	√	√
Observations	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496
R-squared	0.63	0.63	0.63	0.64	0.64	0.64	0.64	0.64

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

Table F.6: Productivity and Technology Sophistication Controlling for ln(K/L) and ln(Labor Cost/L), GBF and SSBF EXT

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
ln(K/L)	0.14***	0.14***	0.14***
	(0.03)	(0.03)	(0.04)
ln(Labor Cost/L)	0.68***	0.68***	0.69***
	(0.04)	(0.04)	(0.04)
GBF EXT	0.65**		
	(0.29)		
GBF EXT^2	-0.08*		
	(0.04)		
GBF MOST		0.93**	
		(0.45)	
GBF MOST^2		-0.16*	
		(0.09)	
GBF GAP		0.12	
		(0.09)	
GBF EXT*AGRI			-0.22
			(0.18)
GBF EXT*MANF			0.24***
			(0.07)
GBF EXT*SVC			0.14*
			(0.08)
SSBF EXT*Agriculture	-0.23	-0.20	0.10
	(0.23)	(0.23)	(0.26)
SSBF EXT*Food Processing	0.25	0.26	0.22
	(0.16)	(0.16)	(0.16)
SSBF EXT*Apparel	0.12	0.10	0.06
	(0.09)	(0.09)	(0.09)
SSBF EXT*Retail and Wholesale	0.10	0.08	0.09
	(0.12)	(0.12)	(0.12)
SSBF EXT*Other Manufacturing	0.02	0.02	-0.01
	(0.05)	(0.05)	(0.05)
SSBF EXT*Other Services	0.15	0.17	0.17
	(0.13)	(0.13)	(0.14)
Var(ABF EXT)	0.27***	0.30***	0.31***
	(0.10)	(0.09)	(0.09)
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. Robust standard errors in parentheses. 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, moto-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.

Table F.7: Productivity and Technology Sophistication Controlling for ln(K/L) and ln(Labor Cost/L), GBF and SSBF MOST

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)
ln(K/L)	0.14***	0.14***
	(0.03)	(0.03)
ln(Labor Cost/L)	0.67***	0.67***
	(0.04)	(0.04)
GBF EXT	0.66**	
	(0.29)	
GBF EXT^2	-0.08*	
	(0.04)	
GBF EXT*AGRI		0.92**
		(0.45)
GBF EXT*MANF		-0.16*
		(0.09)
GBF EXT*SVC		0.14
		(0.09)
SSBF MOST*Agriculture	-0.22	-0.20
	(0.21)	(0.21)
SSBF MOST*Food Processing	0.35**	0.35**
	(0.17)	(0.17)
SSBF MOST*Apparel	0.26**	0.23**
	(0.12)	(0.12)
SSBF MOST*Retail and Wholesale	0.09	0.06
	(0.14)	(0.14)
SSBF MOST*Other Manufacturing	0.10	0.09
	(0.08)	(0.08)
SSBF MOST*Other Services	0.08	0.08
	(0.13)	(0.14)
Var(ABF EXT)	0.28***	0.30***
	(0.10)	(0.09)
Firm Characteristics	√	√
Observations	2,496	2,496
R-squared	0.64	0.64

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

Table F.8: Productivity and Technology Sophistication, GBF and SSBF EXT, Disaggregated Agriculture Sector

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
GBF EXT	1.72***		
	(0.32)		
GBF EXT^2	-0.20***		
	(0.05)		
GBF MOST		1.93***	
		(0.45)	
GBF MOST^2		-0.28***	
		(0.09)	
GBF GAP		0.38***	
		(0.10)	
GBF EXT*AGRI			0.46**
			(0.23)
GBF EXT*MANF			0.61***
			(0.08)
GBF EXT*SVC			0.49***
			(0.09)
SSBF EXT*Agriculture	0.34*	0.44**	0.46*
	(0.21)	(0.20)	(0.26)
SSBF EXT*Livestock	0.30	0.37	0.36
	(0.48)	(0.47)	(0.47)
SSBF EXT*Food Processing	0.30*	0.32*	0.28
	(0.18)	(0.18)	(0.18)
SSBF EXT*Apparel	0.44***	0.40***	0.36***
	(0.11)	(0.10)	(0.11)
SSBF EXT*Retail and Wholesale	-0.02	-0.07	-0.05
	(0.11)	(0.11)	(0.12)
SSBF EXT*Other Manufacturing	0.07	0.05	0.02
	(0.05)	(0.05)	(0.05)
SSBF EXT*Other Services	0.55**	0.58**	0.61***
	(0.23)	(0.23)	(0.23)
Var(ABF EXT)	0.29***	0.36***	0.39***
	(0.10)	(0.10)	(0.10)
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. Robust standard errors in parentheses. 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, moto-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.

Table F.9: Productivity and Technology Sophistication, GBF and SSBF MOST Technology, Disaggregated Agriculture Sector

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)
GBF EXT	1.72***	
	(0.32)	
GBF EXT^2	-0.20***	
	(0.05)	
GBF EXT*AGRI		1.96***
		(0.45)
GBF EXT*MANF		-0.29***
		(0.09)
GBF EXT*SVC		0.38***
		(0.10)
SSBF MOST*Agriculture	0.55***	0.63***
	(0.20)	(0.20)
SSBF MOST*Livestock	-0.05	0.04
	(0.56)	(0.58)
SSBF MOST*Food Processing	0.36**	0.38**
	(0.19)	(0.19)
SSBF MOST*Apparel	0.65***	0.60***
	(0.15)	(0.15)
SSBF MOST*Retail and Wholesale	-0.05	-0.15
	(0.15)	(0.16)
SSBF MOST*Other Manufacturing	0.15*	0.12
	(0.09)	(0.08)
SSBF MOST*Other Services	0.49*	0.48
	(0.29)	(0.30)
Var(ABF EXT)	0.30***	0.37***
	(0.10)	(0.10)
Firm Characteristics	√	√
Observations	2,746	2,746
R-squared	0.50	0.50

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

Table F.10: Productivity and Technology Sophistication, GBF and SSBF EXT Technology, Disaggregated Sectors

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)	(3) ln(VAPW)
GBF EXT	1.70***		
	(0.32)		
GBF EXT^2	-0.20***		
	(0.05)		
GBF MOST		1.89***	
		(0.45)	
GBF MOST^2		-0.27***	
		(0.09)	
GBF GAP		0.37***	
		(0.10)	
GBF EXT*AGRI			0.46**
			(0.23)
GBF EXT*MANF			0.61***
			(0.08)
GBF EXT*SVC			0.49***
			(0.09)
SSBF EXT*Agriculture	0.34*	0.44**	0.46*
	(0.21)	(0.20)	(0.26)
SSBF EXT*Livestock	0.30	0.37	0.36
	(0.48)	(0.47)	(0.47)
SSBF EXT*Food Processing	0.30*	0.32*	0.28
	(0.18)	(0.18)	(0.18)
SSBF EXT*Apparel	0.44***	0.40***	0.36***
	(0.11)	(0.10)	(0.11)
SSBF EXT*Motor Vehicles	0.64***	0.55***	0.55***
	(0.17)	(0.16)	(0.16)
SSBF EXT*Pharmaceuticals	0.29*	0.25	0.22
	(0.16)	(0.16)	(0.16)
SSBF EXT*Retail and Wholesale	-0.02	-0.07	-0.04
	(0.11)	(0.11)	(0.12)
SSBF EXT*Financial Services	1.15**	1.18**	1.25***
	(0.47)	(0.48)	(0.47)
SSBF EXT*Land Transport	0.38	0.44	0.45
	(0.33)	(0.33)	(0.33)
SSBF EXT*Health Services	-0.62*	-0.65*	-0.70*
	(0.37)	(0.37)	(0.37)
SSBF EXT*Leather	-0.47***	-0.51***	-0.53***
	(0.16)	(0.15)	(0.16)
SSBF EXT*Other Manufacturing	0.07	0.05	0.02
	(0.05)	(0.05)	(0.06)
SSBF EXT*Other Services	-	-	-
Var(ABF EXT)	0.28***	0.36***	0.38***
	(0.10)	(0.10)	(0.10)
Firm Characteristics	√	√	√
Observations	2,746	2,746	2,746
R-squared	0.51	0.50	0.50

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

Table F.11: Productivity and Technology Sophistication, GBF and SSBF MOST Technology, Disaggregated Sectors

VARIABLES	(1) ln(VAPW)	(2) ln(VAPW)
GBF EXT	1.70***	
	(0.32)	
GBF EXT^2	-0.20***	
	(0.05)	
GBF EXT*AGRI		1.93***
		(0.45)
GBF EXT*MANF		-0.28***
		(0.09)
GBF EXT*SVC		0.37***
		(0.10)
SSBF MOST*Agriculture	0.55***	0.63***
	(0.20)	(0.20)
SSBF MOST*Livestock	-0.05	0.04
	(0.56)	(0.59)
SSBF MOST*Food Processing	0.36**	0.38**
	(0.19)	(0.19)
SSBF MOST*Apparel	0.65***	0.60***
	(0.15)	(0.15)
SSBF MOST*Motor Vehicles	0.90***	0.73***
	(0.30)	(0.28)
SSBF MOST*Pharmaceuticals	0.26	0.21
	(0.16)	(0.17)
SSBF MOST*Retail and Wholesale	-0.04	-0.14
	(0.15)	(0.16)
SSBF MOST*Financial Services	2.42***	2.44***
	(0.59)	(0.60)
SSBF MOST*Land Transport	0.44	0.47
	(0.40)	(0.40)
SSBF MOST*Health Services	-0.56	-0.69**
	(0.36)	(0.35)
SSBF MOST*Leather	-0.63***	-0.72***
	(0.15)	(0.16)
SSBF MOST*Other Manufacturing	0.16*	0.13
	(0.09)	(0.08)
SSBF MOST*Other Services	-	-
Var(ABF EXT)	0.30***	0.37***
	(0.10)	(0.10)
Firm Characteristics	√	√
Observations	2,746	2,746
R-squared	0.51	0.51

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

Table F.12: Development Accounting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
P10	-0.45	-0.54	-0.51	-0.55	-0.54	-0.56	-0.57	-0.61	-0.58	-0.58	-0.52
P90	0.52	0.48	0.51	0.48	0.54	0.56	0.49	0.53	0.51	0.52	0.55
% Productivity Dispersion Accounted by Technology	31%	33%	33%	33%	35%	36%	34%	37%	35%	36%	34%

Note: Each row presents development accounting associated with each specification used in Table 8 columns (1)-(8) and Table 9 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 columns provide the P10 and P90 of the predicted residuals of ln(vapw), respectively. Third column 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).

Table F.13: Ratio of Predicted Average Productivity: Agriculture vs. Non-Agriculture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGRI	1.61	1.59	1.64	1.59	1.63	1.62	1.60
Non-AGRI	0.99	0.99	0.99	0.99	0.98	0.99	0.99
AGRI/Non-AGRI	1.63	1.61	1.66	1.61	1.66	1.64	1.62
% Accounted by Data	27%	27%	29%	27%	29%	28%	27%

Note: Each column presents each specification used in Table 12 columns (1)-(5) and Table 13 columns (1)-(2) in order.

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