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A The FAT Survey

This section provides more details on the Firm Adoption of Technologies (FAT) survey and its implementation. We start with a description of the grid of technologies in FAT. Then we describe the sampling frames used and the construction of sampling weights. We finalize describing all the tests conducted to minimize potential biases, including validation exercises ex-post implemented with external data sources.

A.1 The Survey

The FAT survey is a multi-country, multi-sector, representative firm-level survey. It collects information on the technologies used by firms in specific business functions that encompass the key activities that each firm conducts. Compared to existing firm-level surveys, the FAT survey covers a significantly larger number of technologies and business functions (Table A.1), and a wider range of sectors; for example, it covers agriculture distinguishing between crops and livestock.

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

Surveys	# of Technologies	# of Business Functions	Includes Firms in Agriculture
Firm-level Adoption of Technology (FAT) Survey	305	63	Yes
Manufacturing Technology Survey (MTS)	17	0	No
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) 2018 Technology module	10	0	No
Annual Business Survey (ABS) 2019 Technology module	5	0	No

Note: The Number of technologies and business functions are computed by authors. MTS, ICTS, and ABS were conducted by the United States Census Bureau. SAT was conducted by the Statistics Canada. ICT Usage in Enterprise is conducted by EUROSTAT.

The FAT survey addresses important knowledge gaps compared to other surveys measuring technology at the firm or establishment level. To start, 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 analyze 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.

Specifically, the FAT survey comprises five sections:

- Module A– Collects general information about the characteristics of the establishment; such as sector, multi-establishment and ownership.
- Module B – Covers the technologies used in seven general business functions.
- Module C – Covers the use of technologies for functions that are specific to each of 11 agriculture, manufacturing, and services sectors.
- Module D – Includes questions about the drivers and barriers for technology adoption.
- Module E – Collects information on employment, financial statements and performance, which allow us to compute labor productivity and other measures at the establishment level.

A.1.1 The Grid

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

First, we started with desk research revising the specialized literature identifying business functions and technologies across the value chain.[38] Second, for each sector, as well as for the general business functions, we hold meetings with private sector specialists at the World Bank Group to validate the initial findings and start to define the key business functions and technologies. Third, we hold meetings with Lead and Senior Economists across the World Bank Group, including the International Finance Corporation (IFC), from different fields of specialization and wide experience with sectoral projects in several countries (e.g. agriculture, manufacturing, retail, transport, health, etc.). Fourth, we hold meetings and validation exercises with external senior consultants, with wide experience on the field (e.g.

[38]This process involved the revision of peer-review journals and reports from international organizations and industry associations.

at least 15 years), including experience with firms in developing countries as well as advanced economies.

The source of external senior consultants in the last layer of quality control varied across sector. For agriculture and livestock, the validation exercise was conducted with agricultural engineers and researchers from Embrapa, an agricultural research institution from Brazil. For food processing, wearing apparel, pharmaceutical, transport, and retail, as well as for the general business functions, the team hired external consultants through a large management consultant organization. For automotive sector, the team has hired a senior consultant directly. For health, the team invited directly five physicians with different field of specializations and practical experience in hospitals in clinics in the United States and low income countries in Saharan Africa.

The validation exercise with sector specialists were organized as follows. First, the team would explain the purpose of the project, present the initial findings, and share a draft with identified business functions and technologies associated with them. The sector specialists would have between one and two weeks to reflect on the material to validate them or propose a new combination of business functions and technologies associated with them. After receiving the revised material, a second meeting with sector specialists would be organized with the FAT survey team to discuss the proposal and converge towards an updated combination of business's functions and technologies.

In what follows we describe the grids for both types of business functions.

A.1.2 General Business Functions

Figure 1 in Section 2 shows the 7 general business functions in FAT and the possible technologies used to conduct them. The business functions identified are: business administration (HR processes, finance,accounting), production planning, procurement and supply chain management, marketing and product development, sales, payment methods, and quality control. These are business functions that in addition to being central in the functioning of the firm, are also retained in some capacity (or some tasks) within the firm. The technologies used for these business functions tend to be more available and off-the-shelf technologies, often ICT technologies. For example, for administrative processes, these range from handwritten processes (the least sophisticated) to the use of enterprise resource planning which are software that allow for real time, integrated management of the main business processes. With the help of management consultants, we identify the technologies feasible for each business function and develop similar rankings of sophistication based on the consultants understanding of the number of tasks and complexity that the technologies can handle.

One important characteristic of the grid is that the sophistication rankings are not fully

hierarchical for all business functions. In the case of sales, for example, firms can use various technologies, and while online sales are more sophisticated technologies that sales on the phone or email, there is no clear sophistication ranking between sales made in the company's website or using online platforms; both are complementary. A similar example occurs with payment methods; firms may use a variety of them, often depending on the financial infrastructure in the country.

A key advantage of the grid structure is that it allows to accommodate the use of more than one technology by business function. The survey questionnaire is implemented so respondents are asked first about the use of each of the technologies in the grid. Then, for those technologies selected in each business function, the respondent is asked to identify the one that is more intensively used in implementing the tasks of the business function. Finally, when using one of the most advanced technologies, the respondent is also asked to provide the year of adoption. This allows to uncover new facts about technology adoption and use by allowing to build new measures of technology sophistication at the business function level based on extensive measures, the most sophisticated technology, and intensive measures, the technology used more intensively. It, also allows to calculate measures of diffusion lags for advanced technologies.

A.1.3 Sector Specific Business Functions

For the sector-specific technologies, a similar approach was used to identify key business functions and associated technologies in 12 sectors of activity across agriculture, manufacturing, and services (including agriculture-crops; livestock; food processing; wearing apparel; leather and footwear; automotive; pharmaceuticals; wholesale and retail; transportation; financial services; health services; other manufacturing). One business function, fabrication, was also included for all manufacturing sectors. Identifying key business functions and the frontier in each sector required significant interaction with several sector specialists. These functions tend to be associated with sector-specific production processes.

Here, we present all sector-specific business functions and associated technologies covered by the FAT survey in the first and second phases of data collection. These figures complement the information provided in Section 2, particularly Figure 2, which describes the functions and associated technologies for SSBFs in agriculture, among SSBFs. The complementary information is provided for all SSBFs, including Livestock (Figure A.1), Food Processing (Figure A.2), Wearing Apparel (Figure A.3), Leather and Footwear (Figure A.4), Automotive (Figure A.5), Pharmaceutical (Figure A.6), Wholesale and Retail (Figure A.7), Transportation (Figure A.8), Financial Services (Figure A.9), Health Services (Figure A.10),

and Other Manufacturing (Figure A.11)). [39]

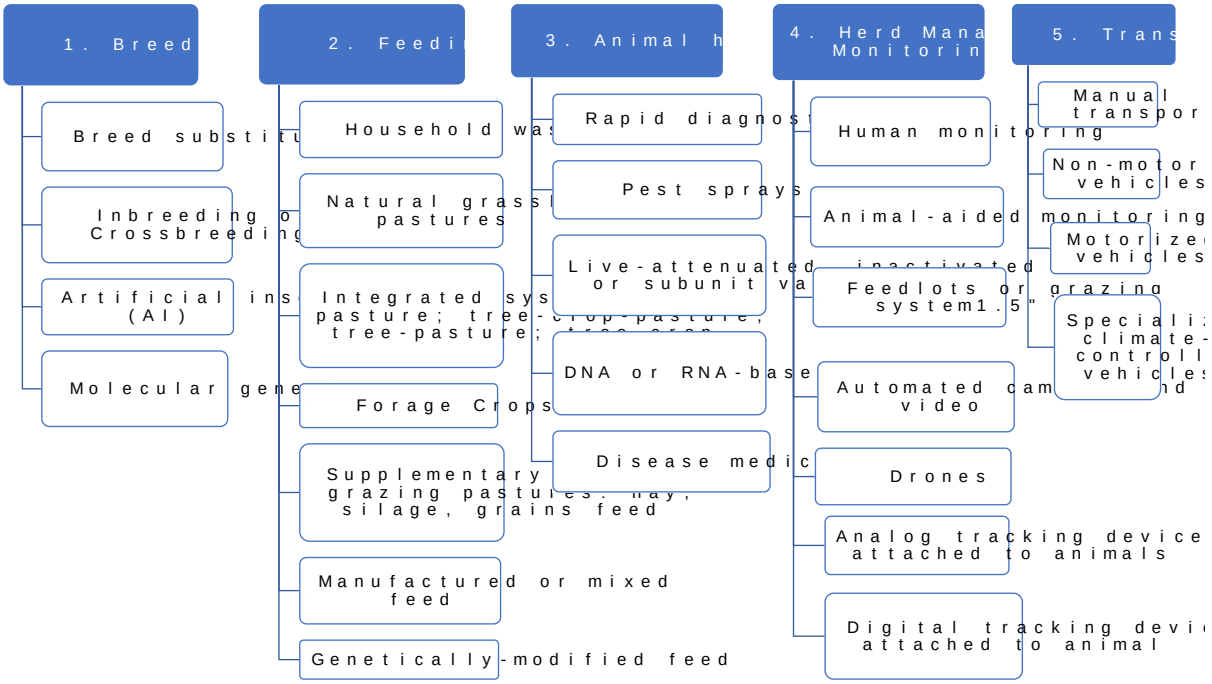


Figure A.1: Agriculture - Livestock: Business Functions and Technologies

[39] As the survey is rolled out in other countries, the number of additional sectors included in the survey is also increasing.

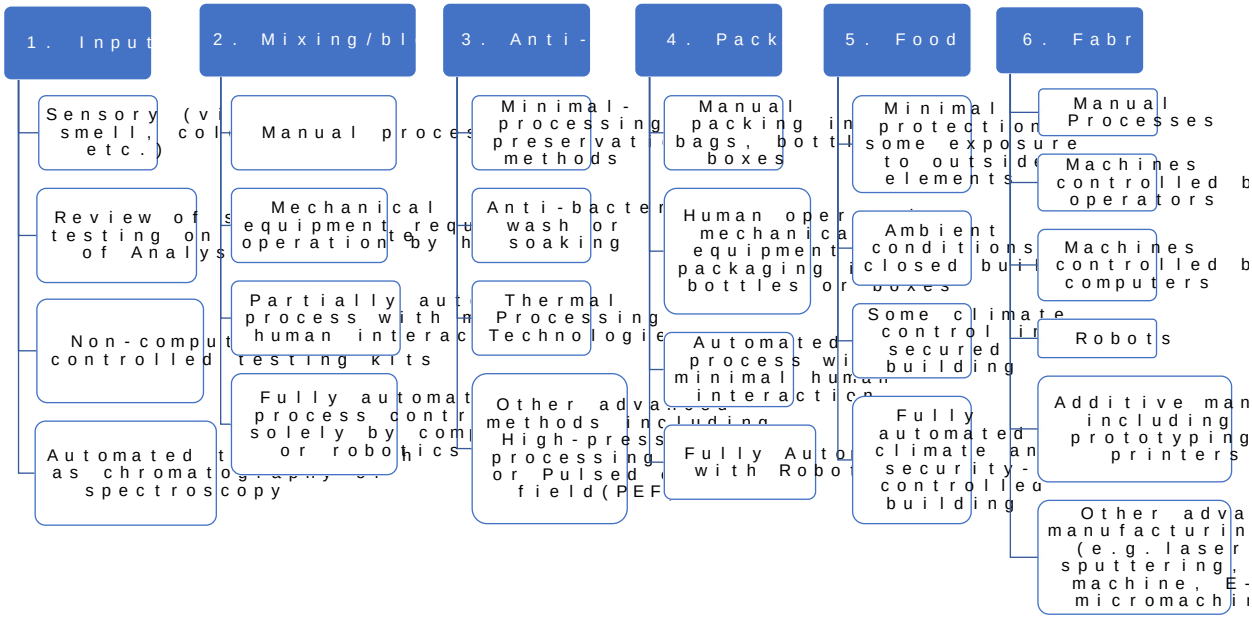


Figure A.2: Food Processing: Business Functions and Technologies

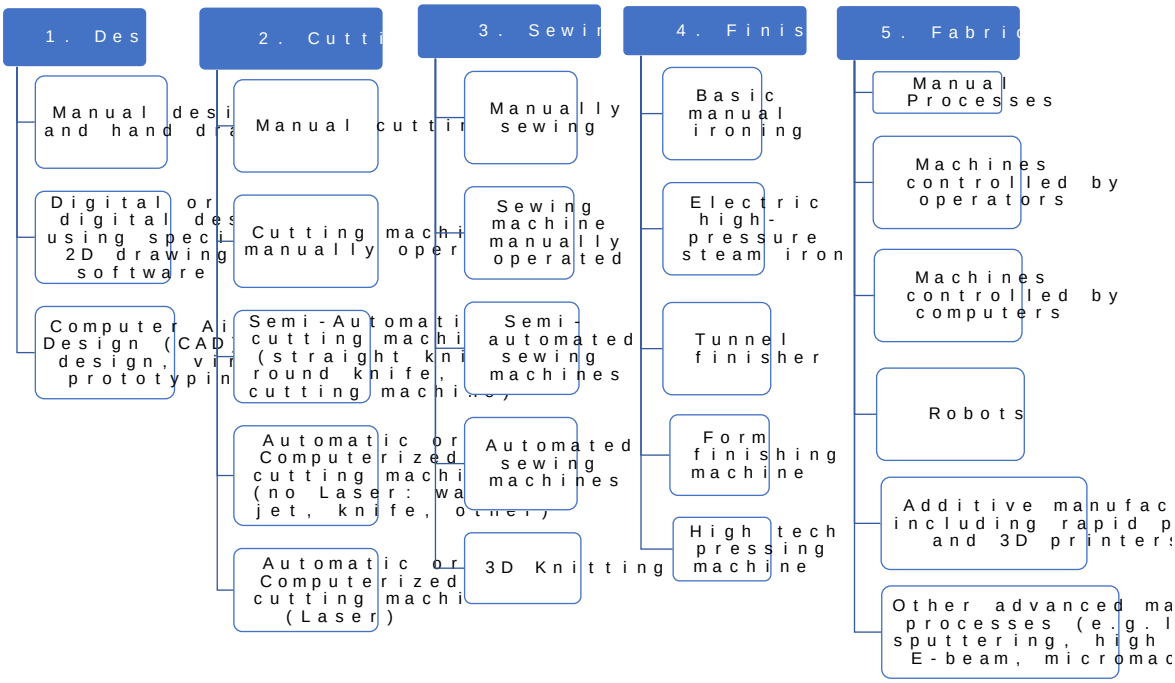


Figure A.3: Wearing Apparel: Business Functions and Technologies

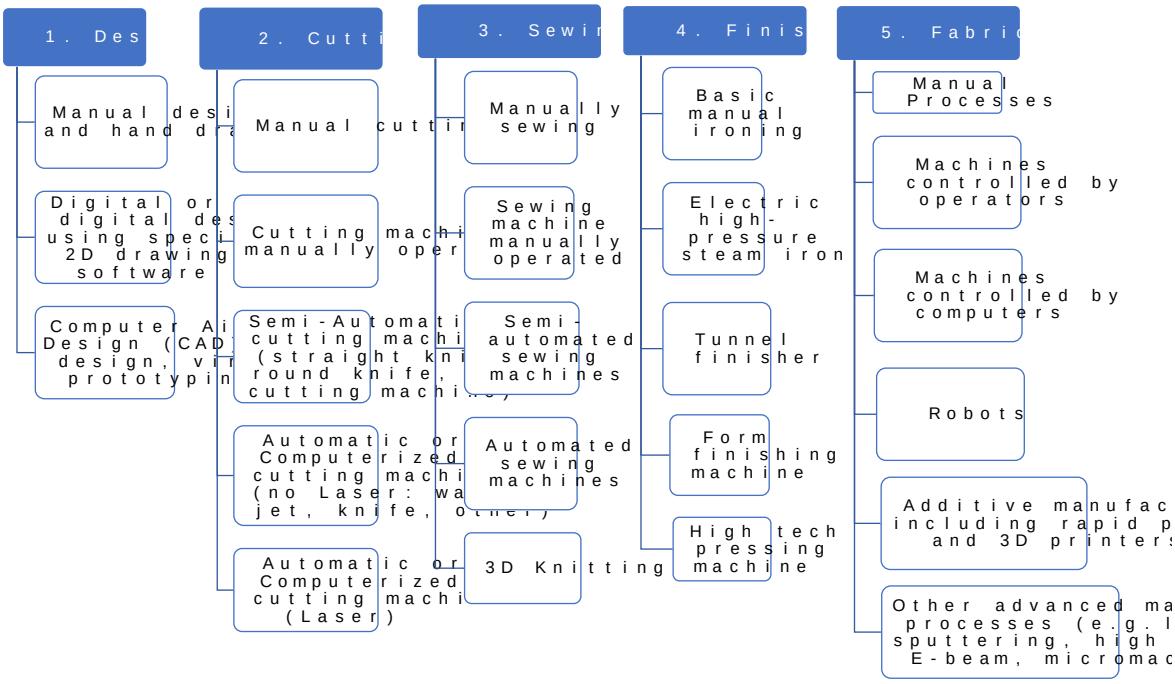


Figure A.4: Leather and Footwear: Business Functions and Technologies

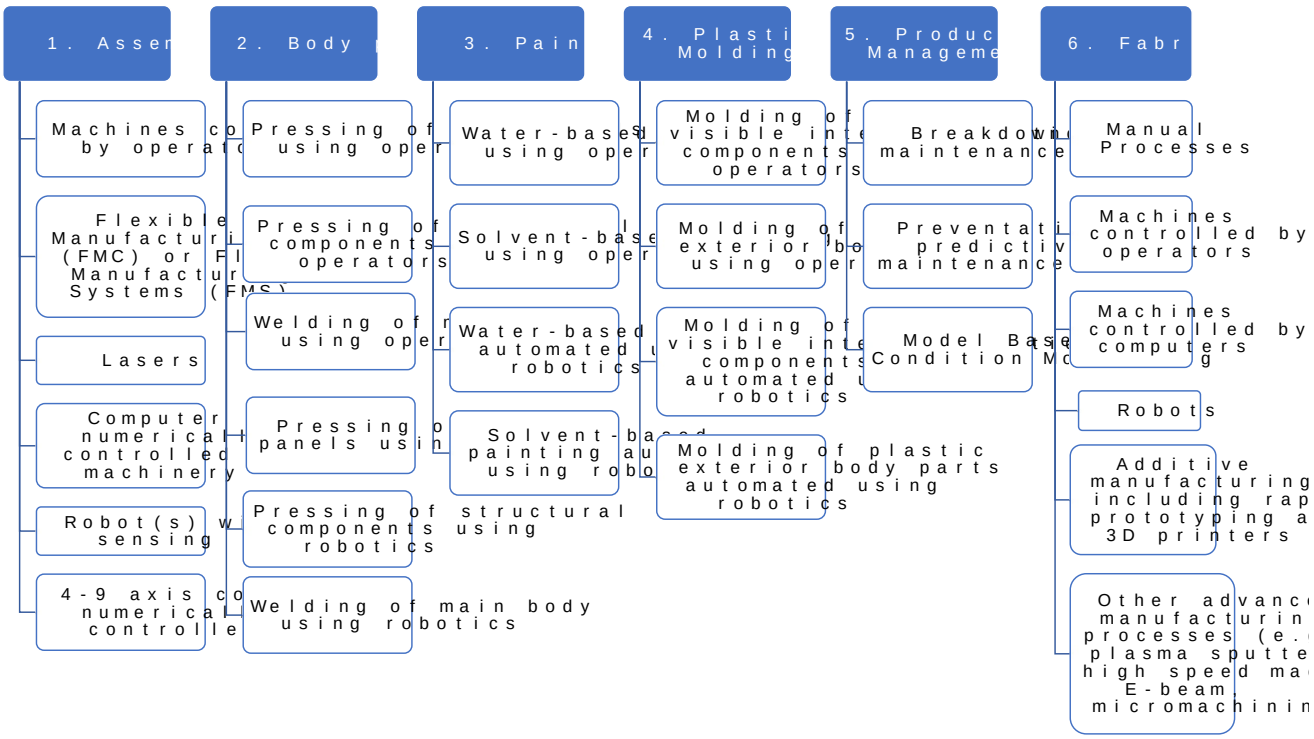


Figure A.5: Automotive: Business Functions and Technologies

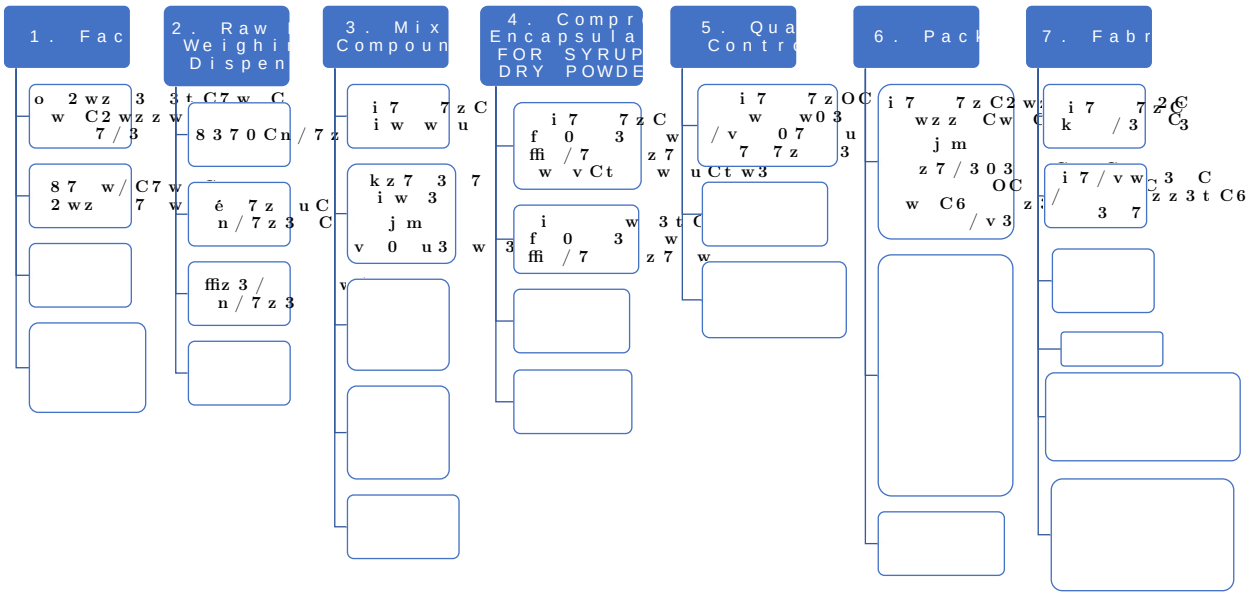


Figure A.6: Pharmaceutical: Business Functions and Technologies

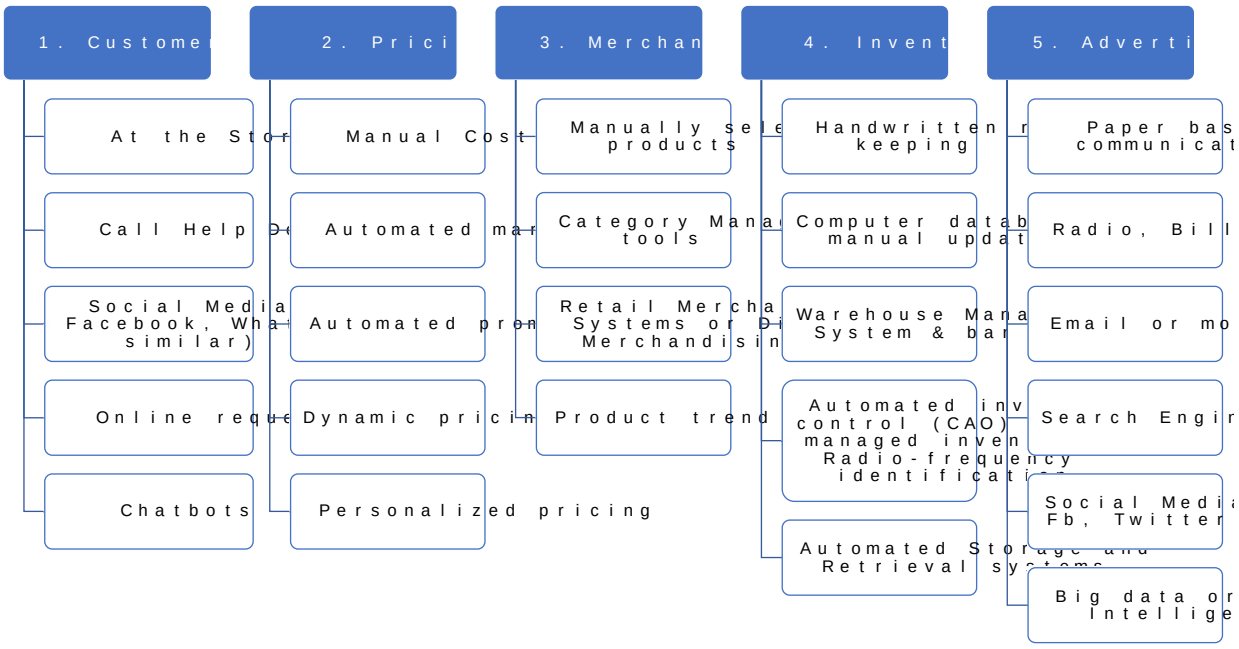


Figure A.7: Wholesale and Retail: Business Functions and Technologies

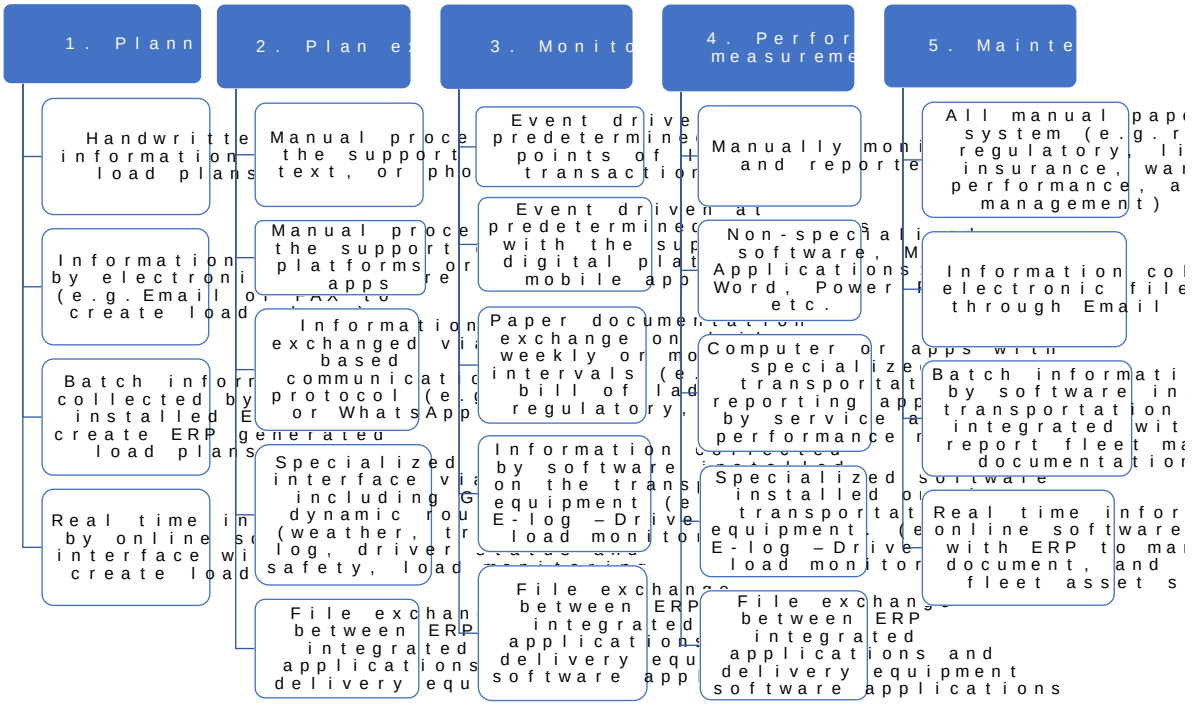


Figure A.8: Land Transportation: Business Functions and Technologies

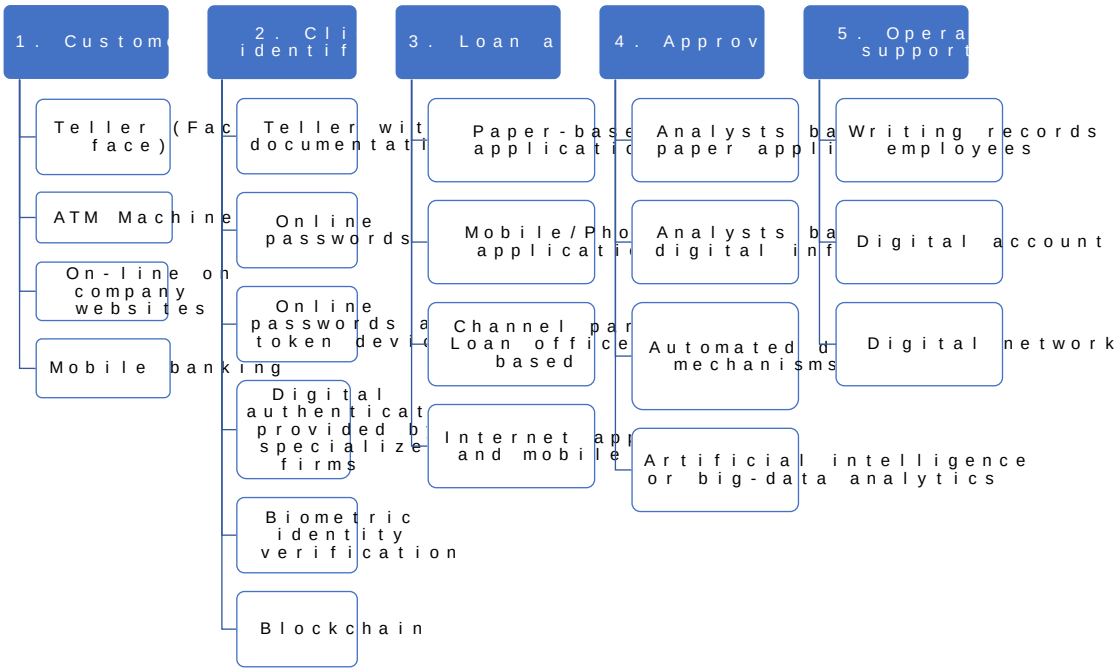


Figure A.9: Financial Services: Business Functions and Technologies

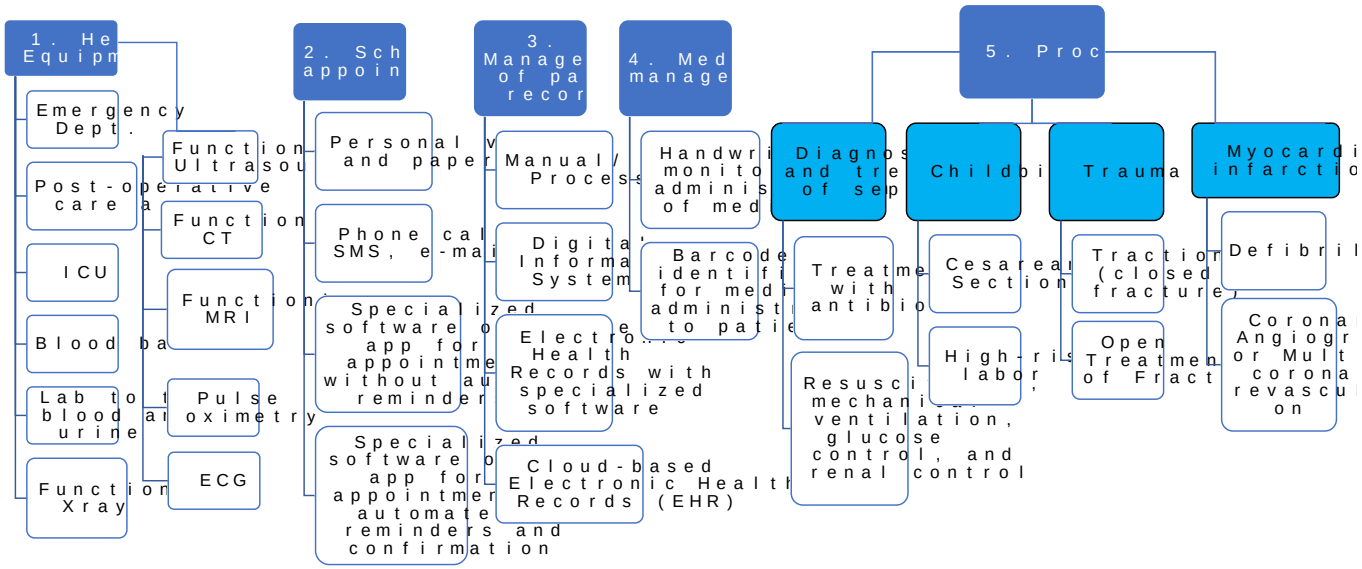


Figure A.10: Health Services: Business Functions and Technologies

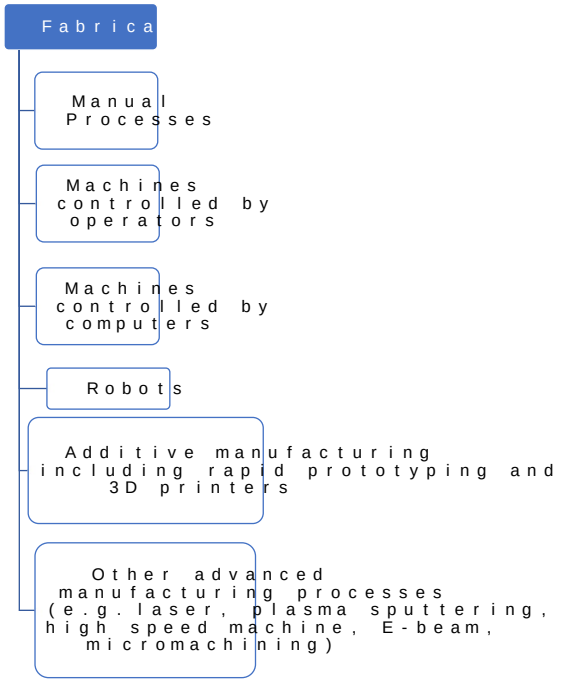


Figure A.11: Other Manufacturing: Business Functions and Technologies

For sector-specific business functions, digital technologies tend to be embedded in other technologies that are usually at the frontier. This is a common feature, particularly in agriculture and manufacturing, and has important implications in terms of the costs of adoption and the importance of network effects. For example, among methods commonly used by agricultural firms to perform harvesting, the most basic option is to harvest manually, followed by animal-aided instruments, human-operated machines, or a single tractor with one specific function (such as a single-axle tractor), a combined harvester (machines or tractors that combine multiple functions fully operated by the worker), and combined harvester using the support of digital technologies (such as global positioning systems [GPS] or computing systems integrated with the tractor). Unlike GBFs, the application of digital technologies for harvesting requires other sophisticated equipment or machines.

In addition to the possibility of computing different measures of technology sophistication for sector specific business functions, an important feature of the sector specific grid is the fact that it includes screening questions that allow for the fact that not all the business functions are carried out within the establishment. In other words, not all entries in the grid need to be implemented at the establishment or at the firm. While the tasks of most general business functions related to management and organization are usually carried out within the boundaries of the firm - either in the same establishment or in another establishment of the firm if multi establishment - some sector specific business functions can be carried out in another establishment within the same firm (insourcing), or they can be (outsourced) to a different firm. Our approach is, therefore, rooted in a view of the firm similar to Coase (1937), where firms are agents coordinating and implementing tasks. The advantage of this approach is twofold. In addition to the fact that this approach allows a better identification of technology and its use as described above, it allows to study critical questions such as the organization of the firm and tasks (Williamson, 1979), and more importantly the relationship between organizational modes, transaction costs and technological choice (Williamson, 1988).

After finalizing the FAT questionnaire, we pre-piloted it in Brazil and Senegal. We personally conducted the face-to-face interviews, in collaboration with enumerators and supervisors trained to conduct data collection with firms from different sectors and size groups. In the pre-pilot stage, we tested if the business functions and technologies covered by the questionnaire were comprehensive and clearly understood by respondents, through detailed discussions and follow up questions with representative of firms, which led us to make the necessary adjustments to the survey. For example, 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 for respondents to answer precisely,

and as a result led to a more subjective interpretation, which made the comparability of answers across business functions and companies harder to interpret.

A.1.4 Barriers and Drivers

In addition to the information on the technologies used by firms, the survey also collects information on potential drivers of and barriers to technology adoption. First, the survey asks whether the firm acquired new machines, equipment, and software in the last three years; and in the case of machines or equipment, whether these were leased, purchased as new or secondhand. The survey also asks questions on links to larger firms and multinationals, either via value chain linkages as a supplier or buyer, or via the CEO previous experience working in a MNE or a large firm.

The survey also asks questions about access to finance and trade status. The first question is about having secured a loan in the previous three years for purchasing equipment, machinery or software. On more general access to finance, the survey asks how many times the establishment needed to borrow money to expand production but could not obtain finance. On trading status, the survey asks whether the firm is an importer, an exporter; and if an exporter, what is the share of sales that is exported.

A key complementary factor for technology adoption is the quality of management. The survey pays special attention to management by collecting information on the top manager's background and on management practices. Specifically, FAT asks about the level of education attainment of the top manager in the establishment, whether she has studied abroad, and whether she has experience in multinationals. In addition, the survey contains four questions about management practices. These include four questions from MOPS (Bloom et al., 2016) on the number of KPIs, the frequency with which they are monitored, the horizon of production targets and a question on the use of formal incentives. Though the information we collect on management practices is more restricted than the sixteen questions in MOPS, we have used information from the Mexico ENAPROCE survey and show that the index that emerges from the small number of variables collected is highly correlated with the full MOPS index and it captures a large fraction of the cross-firm variance in the quality of management practices.[40]

To investigate also the potential role of policies on technology adoption, the survey asks questions about awareness about existing public programs to support technology upgrading;

[40]Specifically, we use data from Mexico ENAPROCE survey and calculate the correlation between a management quality index with the 4 questions in FAT and the overall index using all questions of MOPS that are in ENAPROCE. The correlations are 0.74 for 2015 survey and 0.73 for 2018; which suggests that with less questions we are still able to capture most of the variation in management quality.

and whether the firm is a beneficiary of such programs, and if so, what type of support the firm received.

While the approach of the survey is as much as possible to ask factual questions, it is also important to understand the perceptions that entrepreneurs and managers have about what are the main barriers and drivers of the decisions to adopt new technologies. To this end, the questionnaire asks the respondent to select the most important obstacle and driver for adoption from a closed list of options. As barriers we include: lack of information and technical skills, uncertainty about demand, cost, lack of finance, government regulations or lack of infrastructure. As drivers, we include competition, adoption by other firms, production of new products, accessing new markets, cost reductions or adjusting to regulations. The survey also asks managers to benchmark their business technology sophistication level in relation to other firms in the country, and also vis-a-vis more advanced firms internationally. This helps to understand the role of beliefs of the main managers in technology adoption decisions and potential behavioral biases and overconfidence.

A.1.5 Financial Statements and Workers

In addition to the information on the technologies used by firms, the survey also collects financial statements information, information on the business owners, employees, and on potential drivers of and barriers to technology adoption.

Financial statements. The survey asks the establishment about its total sales, material inputs, replacement value of capital stock, energy consumption, wages and employment. This allows to construct measures of nominal value added per worker, and capital per worker.

Workers. Beyond the number of employees, the survey asks questions that provide information on the education of the workers (share of workers with primary, secondary and tertiary education), and about the occupation composition of the labor force (share of Managers, Professionals, and Technicians; Clerical support workers and sales workers; Production workers and Service workers).

A.2 Validation of the Ranking of Technology Sophistication

To evaluate the coherence of the rankings of technology sophisticated from industry experts, we implement a multi-stage validation exercise. First, we select 14 business functions for which we compare the technologies in the grid along three dimensions that define their sophistication and that summarize some of the arguments used by experts to justify their rankings: functionality, integration, and automation. Functionality refers to the capabilities a technology offers to handle more complex tasks, in a faster way, on a larger scale, with

greater accuracy and reliability. Integration reflects a technology's ability to connect and interact seamlessly with other systems by exchanging data and coordinating processes. Automation enables the technology to execute processes, make decisions, and generate outcomes independently, without human intervention.

For these functions, we also document the year of the launch and the cost of each of the technologies in the grid. Though these variables do not define the sophistication of a technology per se, more sophisticated technologies tend to have been developed more recently and be more expensive. This is particularly the case for sector specific technologies used in the production of goods (e.g., agriculture and manufacturing).

We relied on multiple source collect information on the functionality, integration, and automation features, as well as the launch and the cost of the technologies in the grid. In addition to broad desk research, we consult official websites with description of specific leading brands supplying these technologies (e.g., Microsoft website provides detailed information on the features of Microsoft Excel, including prices, which is used as a *proxy* for standard spreadsheet software, one of the technologies in the grid for business administration).

In addition, we validate the rankings by using AI-powered large language models. First, we asked ChatGPT to rank the technologies in the grid in terms of technology sophistication. Second, we ask ChatGPT to rank technology sophistication based on specific definitions of functionality, integration, and automation and compare those with the industry experts rankings resulted in the technology grid, based on the methodology we described in section 2. Third, we ask ChatGPT to identify a specific task for each of the 14 business functions and estimate the time required to perform the task with each technology.

Tables A.1 - A.13 summarize these exercises for the following business functions: sourcing, marketing, sales, payment, and quality control, among GBFs; Weeding and harvesting for agriculture; Design and sewing for apparel; Anti-bacterial and packaging for food processing; Pricing and inventory for retail services; in addition to the example for businesses administration, provided in section 2. We also added for each business function a summary of two of the exercises with ChatGPT: i) The overall ranking of technology sophistication; ii) The estimated time to perform a typical task in the business function. Next sub-section provides more details on these and additional exercises conducted with ChatGPT. Subsection A.2.1 describes the specific ChatGPT prompts used for these exercises and displays scatter plots showing the positive association between ChatGPT and industry expert rankings of technology sophistication.

Overall, the validation exercise across 14 business functions strongly supports the experts original ranking of sophistication.

Table A.1: Technology Sophistication in Sourcing

	Manual Search	**Computers with Standard Software**	**Mobile Apps or Digital Platforms**	**SRM (not integrated)**	**SRM (integrated with production planning)**
Functionality	Basic functions (e.g., manually finding suppliers in the yellow list)	Moderate features for tracking supplier information and managing procurement database.	Good features for discovering suppliers, comparing options, and managing basic procurement tasks.	Extensive features for supplier management, procurement, contract management, and performance monitoring.	Comprehensive features for supplier management, procurement, contract management, and performance monitoring.
Integration	No.	Limited. It requires manual import/export functions and data entry.	Integrates well with other digital tools, but lacks customization.	Good integration with other procurement tools, but not with production planning.	Seamless integration with production planning and other systems.
Automation	No.	Basic automation through formulas and macros; extensive manual setup and maintenance are required.	Moderate level of automation for tasks such as supplier searches, basic order processing, and communication.	Advanced automation for supplier selection, order processing, and performance tracking.	High level of automation for tasks such as supplier selection, order processing, performance tracking, and demand forecasting.
Rank	1	2	3	4	5
Reason for the Rank	Least sophisticated due to complete lack of integration and automation, relying entirely on manual processes.	Low sophistication due to limited integration and basic automation, mainly suitable for small-scale or manual procurement processes.	Moderate sophistication with decent integration and automation, but mainly focused on task management and basic procurement functions.	Sophisticated in supplier management and procurement with advanced automation, but lacks integration with production planning, limiting its overall functionality.	High level of sophistication with specialized integration for production planning and robust automation, though focused on supplier management and production-related tasks.
Technology Examples	Phone Calls, Personal Visits, Supplier Catalogs	Microsoft Excel (1985), Google Sheets (2006), LibreOffice Calc (2011)	LinkedIn (2003), ThomasNet (1898), Alibaba (1999)	SAP Ariba (1996), Oracle Procurement Cloud (2010), Coupa (2006)	SAP Integrated Business Planning (2014), Oracle SCM Cloud (2016), Infor Nexus (2019)
Cost	Cost of phone calls, travel, accommodation, and catalogs varies	Microsoft Excel: \$150/year, Google Sheets: Free or \$6-\$18/user/month, LibreOffice Calc: Free	LinkedIn: \$59/month, ThomasNet: Free or Custom Pricing, Alibaba: Transaction fees (varies)	SAP Ariba: Pricing depends on enterprise size; Oracle Procurement Cloud: Starts at \$625/user/month, Coupa: \$2,500/month	SAP IBP: Starts at \$30,600/year; Oracle SCM Cloud: Starts at \$350/month; Infor Nexus: Starts at \$10,000
Launch Year	N/A	1985, 2006, 2011	2003, 1898, 1999	1996, 2010, 2006	2014, 2016, 2019
ChatGPT ranking	1	2	3.5	4	5

Source: The table draws upon various sources of information including desk research, website of various companies including Microsoft, Google, LinkedIn, ThomasNet, Alibaba, Oracle, Coupa, InforNexus, and SAP. The prompt for the CHATGPT ranking is available in the appendix.

Table A.2: Technology Sophistication in Marketing

	Face-to-face chat	**Online chat**	**Structured surveys**	**Customer Relationship Management software (CRM)**	**Big Data Analytics or Machine Learning algorithms (AI)**
Functionality	Collecting qualitative data, gaining in-depth insights, building rapport with customers.	Real-time communication with customers, collecting feedback, handling customer queries.	Designing surveys, collecting structured feedback, analyzing responses.	Managing customer data, tracking interactions, automating marketing campaigns, analyzing customer behavior.	Advanced analytics, machine learning, predictive modeling, real-time data processing.
Integration	No integration	Basic integration with CRM systems and data analysis tools.	Moderate integration with data analysis tools and CRM systems.	Good integration with other business systems, including email marketing, social media, and sales platforms.	Seamless integration with multiple data sources, CRM systems, and marketing platforms.
Automation	No automation	Basic automation for responses and data collection; advanced features available in some tools.	Moderate level of automation for survey distribution and response collection, but manual analysis is often required.	High level of automation for tracking interactions, segmenting customers, and running marketing campaigns.	High level of automation for data collection, analysis, and generating insights.
Rank	5	4	3	2	1
Reason for Ranking	Least sophisticated due to the absence of integration and automation, although valuable for qualitative insights.	Effective for immediate customer interaction but lacks the sophistication in automation and integration of higher ranks.	Useful for structured feedback, but lower automation and integration limit its sophistication compared to top ranks.	Strong integration and automation, making it highly effective for comprehensive customer management and marketing.	Highest sophistication due to advanced analytics, seamless integration, and high automation for actionable insights.
Technology Examples	In-person Interviews, Focus Groups, Mystery Shopping	WhatsApp Business, Intercom, LiveChat	SurveyMonkey, Qualtrics, Google Forms	Salesforce, HubSpot CRM, Zoho CRM	Google Analytics
Launch Year	N/A	2018 (WhatsApp Business), 2011 (Intercom), 2002 (LiveChat)	1999 (SurveyMonkey), 2002 (Qualtrics), 2008 (Google Forms)	1999 (Salesforce), 2014 (HubSpot CRM), 2005 (Zoho CRM)	2005
Cost	Cost of time and travel (varies), $2,000-$5,000 per session (Focus Groups), $20-$100 per shop (Mystery Shopping)	Free or $5/month (WhatsApp Business), $39-$139/seat/month (Intercom), $20-$59/user/month (LiveChat)	Free or $25-$75/user/month (SurveyMonkey), Based on invitation (Qualtrics), Free or up to $18/user/month (Google Forms)	$1,000-$10,000/month (Salesforce), $1,170-$4,300/month (HubSpot CRM), Free or $20-$50/user/month (Zoho CRM)	Free or $150,000/year
ChatGPT ranking	1	2	3	4	5

Source: The table draws upon various sources of information including desk research, and websites of various companies including Google, Salesforce, Hubspot, Zoho, SurveyMonkey, Qualtrics, WhatsApp, Intercom, and LiveChat. The prompt for the CHATGPT ranking is available in the appendix.

Table A.3: Technology Sophistication in Sales

	Sales at the establishment's premises	**Sales by phone, email orders, or sales representatives**	**Sales through social platforms**	**Online sales using external digital platforms**	**Online sales (own website)**	**Electronic orders integrated to SCM systems**
Functionality	Basic features for point of sale, inventory management, and sales tracking.	Features for managing customer data, tracking sales activities, and automating sales processes.	Basic features for creating online storefronts, managing product listings, and processing sales orders.	Features for listing products, managing inventory, processing orders, and handling shipping and returns.	Extensive features for creating and managing online stores, processing payments, handling shipping, and inventory management.	Comprehensive features for managing e-commerce, order processing, inventory management, and supply chain integration.
Integration	Limited integration with other systems.	No integration with CRM and email systems.	Limited integration with inventory management and processing systems.	Good integration with inventory management and shipping services.	Good integration with payment gateways, shipping carriers, and inventory management systems.	Seamless integration with supply chain, inventory, and logistics systems.
Automation	Basic automation for sales tracking and inventory updates.	Moderate automation for tracking interactions and managing sales activities.	Moderate level of automation for order processing and inventory updates.	Moderate level of automation for order processing and inventory updates.	High level of automation for order processing, payment handling, and inventory updates.	High level of automation for order processing, inventory updates, and supply chain management.
Rank	6	5	4	3	2	1
Reason	Basic functionality and minimal integration or automation, suitable for traditional retail.	Limited sophistication due to lack of integration, with moderate automation focusing on sales tracking.	Moderately sophisticated with strong integration and moderate automation, suitable for third-party selling.	High sophistication with extensive e-commerce functionality, good integration, and significant automation.	High sophistication with e-commerce integration and automation	Most sophisticated due to its comprehensive functionality, seamless integration with supply chains, and high automation.
Technology Example	Offline stores	WhatsApp/ Email/ Salesmen	Facebook Shops	Amazon Seller Central	Shopify	SAP Commerce Cloud
Cost	Cost of setting up stores	Cost of mobile, internet, travel	Facebook Shops	\$39.99/month + selling fees	\$29-\$299/month	Starts at \$100,000/year
Launch Year	n/a	n/a	2020	2000	2006	2013
ChatGPT ranking	1	2	3	4	4.5	5

Source: The table draws upon various sources of information including desk research, and websites of various companies including SAP, Shopify, Amazon, Facebook, and WhatsApp. The prompt for the CHATGPT ranking is available in the appendix.

Table A.4: Technology Sophistication in Payment

Criteria	**Exchange of goods (Barter Exchange Platforms)**	**Cash(Physical Currency)**	**Cheque, voucher, or bank wire at the branch (Bank Cheque)**	**Prepaid card, Debit card, or Credit card (Visa)**	**Online or electronic payment through a bank wire (SWIFT)**	**Online payment through platform (PayPal)**	**Virtual or Cryptocurrency (Bitcoin)**
Functionality	Facilitating the direct exchange of goods and services without using money	Direct payment using coins and banknotes	Payment through written orders to a bank to pay a specific amount from a person's account	Electronic payment method allowing payment directly from a linked bank account or credit line	Secure international financial messaging for transferring funds between banks	Online payment system for sending and receiving money, purchasing goods and services	Decentralized digital currency for peer-to-peer transactions
Integration	No integration	No integration	Basic integration with banking systems for processing cheques	Wide integration with merchants, banks, and payment processors	Extensive integration with global banking systems	Seamless integration with e-commerce platforms, banking systems, and other financial tools	Good integration with digital wallets, exchanges, and some e-commerce platforms
Automation	No automation	No automation	Limited automation; manual processing required	High level of automation for transaction approval and record-keeping	High level of automation for fund transfers and transaction tracking	High level of automation for transaction processing, payment notifications, and record-keeping	High level of automation for transaction validation and record-keeping via blockchain technology
Rank	7	6	5	4	3	2	1
Reason for Ranking	Basic functionality with no integration or automation, the least sophisticated method in the context of payments	Simple functionality with no integration or automation, making it the least sophisticated	Limited functionality and integration, with minimal automation, making it less sophisticated than newer methods	Widely accepted with robust integration and automation, although slightly less sophisticated than online platforms	Strong integration within global banking, with reliable automation, but more suited for large transactions	High functionality, broad integration across multiple platforms, and high automation in processing payments	High automation, but integration is less widespread and functionality is limited to certain platforms
Average Costs	Transaction fees, varies	No cost	Bank fees, varies	Merchant fees (1.5%-3%), annual fees ($0-$100)	Bank fees, varies	2.9% + $0.30 per transaction	Transaction fees (varies), network fees
Launch Year	N/A	N/A	N/A	1958	1977	1998	2009
ChatGPT ranking	1	2	2.5	3.5	4	4.5	5

Source: The table draws upon various sources of information including desk research, and websites of various companies including Bitcoin, PayPal, SWIFT, and VISA. The prompt for the and CHATGPT ranking is available in the appendix.

Table A.5: Technology sophistication in Quality Control

Category	Manual, Visual or Written Processes	Human Inspection with Computers	Statistical Process Control	Automated Systems for Inspection
Functionality	Documenting inspection results, visual checks, manual recording of defects.	Digitizing inspection processes, capturing photos, real-time data entry.	Analyzing data, statistical process control, generating control charts and reports.	Automated visual inspection, defect detection, measurement, sorting.
Integration	No integration	Moderate integration with data management systems and reporting tools.	Good integration with data collection systems and reporting tools.	High integration with manufacturing systems, data collection, and reporting tools.
Automation	No automation	Moderate level of automation for data entry and reporting; inspections still manual.	High level of automation for data analysis, control chart generation, and reporting.	High level of automation for real-time inspection, defect detection, and data logging.
Rank	4	3	2	1
Reason for Ranking	Lowest sophistication as it lacks automation and integration, relying entirely on manual processes.	Moderately sophisticated with digitized processes but less automated inspection; integration is less robust.	Highly sophisticated with automated data analysis, good integration with data systems, but less real-time functionality compared to automated systems.	Highest sophistication due to full automation and advanced integration with manufacturing systems for real-time inspection and data logging.
Technology Example	Checklists and Written Reports	Inspectorio	Minitab	Cognex In-Sight
Average Costs	Cost of paper and printing, varies	Varies	$1,500-$4,000/license	$5,000-$20,000/system
Launch Year	N/A	2016	1972	2016
ChatGPT ranking	1	2.5	3	4

Source: The table draws upon various sources of information including desk research, and websites of various companies, including Cognex In-Sight, and Minitab, Inspectorio. The prompt for the CHATGPT ranking is available in the appendix.

Table A.6: Technology sophistication in Agriculture - Weeding

	Manual application of herbicide, fertilizer, or pesticide	**Biological methods of fertilizing, weed, or pest control**	**Mechanical application of herbicide, fertilizer, or pesticide**	**Fully-automated VRA tools (Precision Agriculture)**	**Drone Application (Advanced Precision Agriculture)**
Functionality	Simple tools for applying inputs by hand.	Utilizes natural predators and organic materials to enhance soil fertility and control pests.	Mechanized sprayers can cover large areas and apply inputs consistently.	VRA tools adjust the number of inputs based on real-time soil and plant conditions.	Drones can perform a wide range of tasks such as applying inputs, monitoring fields, and collecting data.
Integration	No integration with digital or mechanical systems.	Minimal integration with other systems; relies on natural processes.	Limited integration with digital technologies; primarily mechanical.	Integrated with soil and plant sensors to provide data-driven application rates.	High integration with remote sensing technology and on-site sensors, providing real-time data and analytics.
Automation	Entirely manual; requires significant labor and time.	No automation; requires human oversight and management.	Requires human operation but significantly reduces the physical effort and time.	Automated application based on sensor data, ensuring optimal use of resources.	Highly automated with minimal human intervention, allowing for precise application and monitoring.
Rank	5	4	3	2	1
Reason for Rank	Least sophisticated with basic functionality, no integration, and no automation.	Low sophistication with natural functionality, minimal integration, and no automation.	Moderate sophistication with effective functionality, but limited integration with digital systems and requires human operation.	High sophistication with precise functionality and good integration with digital systems, but slightly less automated and versatile than drones.	Most sophisticated with high functionality, full integration with digital systems, and high automation.
Technology Example	Hand-held Sprayer	Composting and Natural Predators	Tractor-mounted Sprayer	VRA Sprayer with Sensors	Agricultural Drone with Sensors
Average Costs	$20-$100	$50-$500	$1,000-$10,000	$20,000-$50,000	$10,000-$30,000
Launch Year	N/A (Ancient Tool)	N/A (Ancient Practice)	1950s	2000s	2010s
ChatGPT ranking	1	2.5	3	4.5	5

Source: The table draws upon various sources of information including desk research, and websites of various online marketplaces for agricultural tools like Home Depot and Rogers Sprayers. The prompt for the CHATGPT ranking is available in the appendix.

Table A.7: Technology sophistication in Agriculture - Harvesting

	Manual Harvesting, Training, Pruning, or Picking	**Animal Aided Instruments**	**Human-Operated Machines or Single-Axle Tractor (One Specific Function)**	**Mechanized Process (Fully Operated by Worker)**	**Automated Process (Supported by Digital Technologies)**
Functionality	Basic manual tasks (collecting, cutting, pruning).	Performs basic functions with animal assistance (e.g., tilling, transporting).	Performs a specific function (e.g., soil preparation, grass cutting).	Combines cutting, threshing, and cleaning into one operation.	Combines multiple functions (cutting, threshing, cleaning) with high precision.
Integration	No integration, entirely manual.	Limited integration, relies on animal power.	Limited to single-function tasks.	Mechanically integrates multiple harvesting functions.	Integrates GPS and computing systems for optimized paths and resource use.
Automation	No automation, fully reliant on human labor.	No automation, dependent on human and animal labor.	Manually operated, no automation.	Operated manually by the worker, but mechanized.	High level of automation, requiring minimal human intervention.
Rank	5	4	3	2	1
Reason for Rank	Least sophisticated with basic functionality, no integration, and entirely manual labor.	Low sophistication, relying on animal labor with no digital integration or automation.	Moderate sophistication with effective functionality, but limited to single functions and requires full manual operation.	High functionality with integration of multiple mechanical functions, but requires manual operation.	Most sophisticated with advanced functionality, full integration with digital systems, and high automation.
Technology Examples	Harvesting Bags, Felco Pruning Shears, Hori Hori Knife	Horse-Drawn Reaper, Ox-Drawn Mower, Animal-Powered Binder	Walk-Behind Sickle Bar Mower, Single-Axle Mower, Hand-Pushed Seeder	Tractor-Mounted Harvester, Combine Harvester, Self-Propelled Forage Harvester	GPS-Enabled Tractor with Harvesting Attachment, Auto-Steer Combine Harvester, Smart Forage Harvester
Average Costs	$30, $50, $35	$300, $250, $400	$600, $600, $450	$7,000, $300,000, $150,000	$200,000, $400,000, $350,000
Launch Years	1960, 1945, 1950	1800s, 1800s, 1850s	1960s, 1970s, 1960s	1920s, 1930s, 1940s	1990s, 2000s, 2010s
ChatGPT ranking	1	2	3.5	4	5

Source: The table draws upon various sources of information including desk research, and websites of various online sellers of agricultural equipment including John Deere, CLAAS, and Amazon Marketplace. The prompt for the CHATGPT ranking is available in the appendix.

Table A.8: Technology sophistication in Apparel - Design

	Manual design and hand drawing	**Digital or semi-digital design using specialized 2D drawing software**	**Computer Aided Design (CAD), 3D design, virtual prototyping**
Functionality	Fundamental capabilities for drawing and drafting, relying on user skill and precision	Robust capabilities for vector graphics, layout design, and technical drawing	Comprehensive 2D and 3D design features, including advanced modeling, simulation, and rendering
Integration	No digital integration; standalone and physical	Limited integration; can import/export various file types	High integration with CAM, CAE, and other tools for seamless workflow
Automation	No automation; all aspects are manual	Moderate automation with snap-to-grid, alignment tools, and reusable components	High level of automation with automatic dimensioning, constraint management, and generative design
Rank	3	2	1
Reason for Ranking	Lowest sophistication due to reliance on manual input, lack of integration, and absence of automation	Moderate sophistication with strong 2D design capabilities, but lower integration and automation compared to CAD tools	Highest sophistication due to advanced functionality, seamless integration, and high automation, ideal for complex apparel design
Technology Examples	Drafting Table, Mechanical Pencil, Drawing Paper	Adobe Illustrator, CorelDRAW, AutoCAD LT	AutoCAD, SolidWorks, Autodesk Fusion 360
Cost	$2 - $300	$20.99/month - $499 (one-time) or $198/year	$60/month - $3,995 (one-time) + $1,295/year maintenance
Launch Year	N/A	1987 - 1993	1982 - 2013
ChatGPT ranking	1	3	4.5

Source: The table draws upon various sources of information including desk research, and websites of companies like Autodesk, SolidWorks, CorelDraw, and Adobe. The prompt for the CHATGPT ranking is available in the appendix.

Table A.9: Technology sophistication in Apparel - Sewing

	Manually Sewing	**Machine Sewing Manually Operated**	**Semi-automated Sewing Machines**	**Automated Sewing Machines**	**3D Knitting**
Functionality	Basic hand stitching, mending, and precise cutting of fabric.	Basic stitching with manual adjustments for tension and stitch length.	Automatic tension adjustment, multiple stitch patterns, and built-in embroidery designs.	High-speed sewing, automated thread trimming, and programmable stitch patterns.	Knits entire garments in 3D with no seams, enabling complex designs and high customization.
Integration	No integration	Limited to no integration with digital or automated systems.	Integrated with pre-programmed patterns and digital interfaces for ease of use.	Often integrated with manufacturing systems for efficient production workflows.	Integrated with digital design software, allowing for seamless transition from design to production.
Automation	No automation	Minimal automation; relies on user skill and manual adjustments for operation.	Moderate level of automation with features like automatic needle threading and thread cutting.	High level of automation, reducing the need for manual adjustments and interventions.	Fully automated knitting process, from pattern creation to finished garment.
Rank	5	4	3	2	1
Reason for Ranking	Lowest sophistication, entirely manual with no automation or digital integration.	Lower sophistication due to minimal automation and lack of integration with digital systems.	Moderate sophistication with useful automation features, but limited compared to fully automated systems.	High sophistication with advanced functionality and integration, but less specialized than 3D knitting.	Highest sophistication due to full automation, advanced functionality, and seamless integration with digital design tools.
Technology Examples	Needle and Thread, Thimble, Fabric Scissors	Mechanical Sewing Machine, Hand-Crank Sewing Machine, Foot-Pedal Sewing Machine	Electronic Sewing Machine, Computerized Sewing Machine, Embroidery Machine	Industrial Sewing Machine, Automated Quilting Machine, Automated Serger	Shima Seiki Whole-Garment, Stoll ADF 3, Kniterate
Cost	$1 - $30	$100 - $500	$300 - $3,000	$1,000 - $20,000	$7,500 - $250,000
Launch Year	Ancient - N/A	1800s - 1900s	1970s - 1990s	1960s - 2000s	1970s - 2018
ChatGPT ranking	1	2.5	3.5	4.5	5

Source: The table draws upon various sources of information including desk research, and websites of companies like Kniterate as well as online sellers of sewing equipment like Amazon Marketplace. The prompt for the CHATGPT ranking is available in the appendix.

Table A.10: Technology sophistication in Food Processing - Anti-Bacterial

	Minimal-processing Preservation	**Anti-bacterial Wash or Soaking**	**Thermal Processing Technologies**	**Other Advanced Methods (HPP, PEF)**
Functionality	Slows bacterial growth without killing pathogens, preserving food quality.	Reduces bacterial load on food surfaces, effective for surface decontamination.	Effective in killing bacteria and pathogens through heat, ensuring food safety.	HPP and PEF offer advanced bacterial inactivation with minimal impact on food quality. UV treatment provides surface-level decontamination.
Integration	Easy to integrate, requires basic modifications to packaging/storage processes.	Simple to integrate into existing systems with easy-to-implement tanks or spray systems.	Well-integrated in the food industry, adaptable to different production scales.	Moderate to high integration into existing production lines with minimal adjustments required.
Automation	Limited automation potential, requiring manual checks and adjustments.	Can be automated but requires some manual intervention for effective application.	Highly automated, offering precise control over processing conditions.	Fully automated processes requiring minimal human intervention.
Rank	4	3	2	1
Explanation for Ranking	Lower sophistication due to minimal bacterial inactivation and reliance on manual processes for maintaining effectiveness.	Moderate sophistication, as it is effective and easy to integrate, but with lower automation levels and more manual intervention needed.	High sophistication due to reliable pathogen inactivation, well-established integration in the industry, and high levels of automation.	Highest sophistication due to advanced, non-thermal bacterial inactivation methods, high integration potential, and full automation.
Technology Examples	Modified Atmosphere Packaging (MAP), Vacuum Packaging, Edible Coatings	Chlorine Dioxide Wash, Organic Acid Wash, Ozone Treatment	Steam Pasteurization, Infrared Heating, Microwave Pasteurization	High-Pressure Processing (HPP), Pulsed Electric Field (PEF), Ultraviolet (UV) Treatment
Cost	$10,000 - $100,000	$500 - $20,000/year	$50,000 - $500,000	$10,000 - $2,500,000
Launch Year	1980s - 2000s	1990s - 2000s	1980s - 2000s	1990s - 2000s
ChatGPT ranking	2	2.5	4	4.5

Source: The table draws upon various sources of information, including desk research and some lab reports, to provide cost estimates of various anti-bacterial processes. The prompt for the CHATGPT ranking is available in the appendix.

Table A.11: Technology sophistication in Food Processing - Packaging

	Manual Packing in Bags, Bottles, or Boxes	**Human Operated Mechanical Equipment**	**Power Equipment Requiring Routine Interaction**	**Power Equipment Controlled by Computers/Robotics**
Functionality	Basic functionality involving manual sealing of bags, wrapping of products, and application of labels to packages.	Functionality includes weighing and filling of packages, sealing of bags, and capping of bottles with human-operated mechanical equipment.	High functionality with automated processes for bagging, filling, and wrapping, reducing the need for manual effort.	Highest functionality with advanced capabilities such as precise handling, stacking, and packaging with minimal errors.
Integration	No integration, manual processes not typically integrated with automated systems.	Moderate integration, relatively easy to incorporate into existing workflows but still reliant on human operation.	Moderate to high integration, capable of being incorporated into existing systems but requiring human oversight and routine interaction.	High integration complexity but can seamlessly integrate into existing production lines to enhance efficiency and reduce manual labor.
Automation	No automation, entirely dependent on human labor.	Low to moderate automation, with significant human involvement required for operation and control.	High level of automation, but still requires routine human interaction for loading, monitoring, and occasional adjustments.	Highest level of automation, requiring minimal human interaction once programmed and set up.
Rank	4	3	2	1
Reason for Ranking	Lowest sophistication due to full reliance on manual labor with no automation or integration capabilities.	Moderate sophistication due to reliance on human operation with limited automation, improving speed and accuracy compared to manual methods.	High sophistication due to automated processes with significant human oversight and interaction needed.	Highest sophistication due to advanced functionality, seamless integration, and full automation with minimal human interaction.
Technology Examples	Handheld Heat Sealer, Manual Wrapping Machine, Handheld Label Applicator	Mechanical Weighing and Filling Machine, Foot Pedal Operated Heat Sealer, Semi-Automatic Bottle Capping Machine	Automatic Bagging Machine, Automated Filling Machine, Automated Wrapping Machine	Robotic Palletizer, Automated Guided Vehicles (AGVs), Computer-Controlled Packaging Line
Cost	$30 - $300	$1,000 - $10,000	$10,000 - $100,000	$50,000 - $1,000,000
Launch Year	1970s - 1990s	1980s - 2000s	1990s - 2010s	2000s - 2015
ChatGPT ranking	1	2.5	3.5	4.5

Source: The table draws upon various sources of information, including desk research and websites of companies that provide packaging solutions like ZoneSun Auto Pack. The prompt for the CHATGPT ranking is available in the appendix.

Table A.12: Technology sophistication in Retail - Pricing

	Manual Cost	**Automated Markup (Excel or similar)**	**Automated Promotional**	**Dynamic Pricing Systems**	**Personalized Pricing driven by Predictive Analytics**
Functionality	Minimal features, relying entirely on manual calculations and record-keeping.	Provides basic automation for pricing calculations, applying markups, and tracking data using formulas and templates.	Focuses on automating promotional pricing based on predefined rules, events, and seasonal factors.	Utilizes AI to optimize prices based on demand prediction, competitive analysis, and real-time data.	Offers the most advanced features, including personalized pricing strategies based on customer behavior, preferences, and predictive analytics.
Integration	No integration	Limited integration capabilities, mainly requiring manual data import/export.	Good integration with sales, marketing, and e-commerce platforms to manage promotions efficiently.	Integrates well with market data sources and internal business systems to provide comprehensive pricing strategies.	Integrates seamlessly with various data sources, CRM systems, and e-commerce platforms to gather comprehensive customer data.
Automation	No automation, entirely dependent on human labor.	Some automation through formulas, but significant manual effort is required for data entry and maintenance.	Automates promotional pricing adjustments, but typically based on predefined schedules and rules rather than real-time data.	Automated price adjustments based on real-time data and algorithms, requiring minimal manual intervention.	Highly automated, using machine learning algorithms to adjust pricing dynamically in real-time based on predictive models and customer data.
Rank	5	4	3	2	1
Reason for Ranking	Lowest sophistication due to the absence of automation and integration, relying entirely on manual calculations.	Lower sophistication with basic automation and limited integration, relying heavily on manual processes for data management.	Moderate sophistication with strong promotional features but limited real-time automation and integration compared to dynamic pricing systems.	High sophistication with strong automation and integration, optimizing prices based on real-time data and AI algorithms.	Highest sophistication due to advanced personalization, seamless integration with multiple platforms, and full automation using AI.
Technology Examples	Pen and Paper	Microsoft Excel, Google Sheets, QuickBooks	Salesforce CPQ, SAP Hybris, Shopify Plus	PROS Pricing, Dynamic Pricing by Prisync, RepricerExpress	Dynamic Yield, Zilliant, Adobe Target
Cost	Minimal to None	\$160/year (Office), Free to \$12/month, \$25/month	\$75/user/month, Custom pricing, \$2000/month	Custom pricing, \$59/month, \$55/month	Custom pricing
Launch Year	Pre-digital	1983 - 2006	1997 - 2006	1985 - 2014	1999 - 2011
ChatGPT ranking	1	2.5	3	4	5

Source: The table draws upon various sources of information including desk research, and websites of companies like Microsoft, Google, Salesforce, SAP, Adobe, PROS, and RepricerExpress. The prompt for the CHATGPT ranking is available in the appendix.

Table A.13: Technology sophistication in Retail - Inventory

	Handwritten Record Keeping	**Computer Databases with Manual Updates**	**Warehouse Management System**	**Automated Inventory Control**	**Automated Storage and Retrieval Systems (AS/RS)**
Functionality	Basic manual entry and tracking of inventory data.	Basic inventory tracking and data management with manual data entry and updates.	Comprehensive inventory management, order fulfillment, warehouse operations, and supply chain optimization.	Advanced inventory control using RFID for real-time tracking, CAO for automated order replenishment, and VMI for vendor-managed inventory solutions.	Fully automated systems for high-density storage, retrieval, and inventory management.
Integration	No integration	Limited integration capabilities, primarily requiring manual data import/export.	Integrates with ERP, TMS, and other business systems for end-to-end visibility and control.	Integrates with supply chain systems, WMS, and ERP systems for seamless data flow and inventory optimization.	Seamlessly integrates with WMS, ERP, and other business systems to provide real-time data and analytics.
Automation	No automation	Minimal automation, mainly through formulas and templates, with significant manual effort needed.	Offers significant automation for inventory tracking, order processing, and warehouse operations but requires some manual oversight.	High level of automation with real-time tracking, automated updates, and reduced manual intervention.	Provides the highest level of automation, handling storage and retrieval tasks autonomously with minimal human intervention.
Rank	5	4	3	2	1
Reason for Ranking	Lowest sophistication due to the absence of automation and integration, relying entirely on manual processes.	Lower sophistication due to limited automation and integration, with significant manual data entry required.	Moderate sophistication with strong functionality and integration, but with some manual oversight required for operations.	High sophistication due to advanced real-time tracking, automated inventory control, and strong integration with supply chain systems.	Highest sophistication due to full automation, seamless integration, and advanced functionality in high-density storage and retrieval.
Technology Examples	Ledger Books, Paper Forms, Manual Logs	Microsoft Access, Google Sheets, QuickBooks	SAP EWM, Oracle WMS, Manhattan WMS	Zebra Technologies, Blue Yonder, IBM Sterling	Swisslog, Dematic, Honeywell Intelligrated
Cost	Minimal	\$160/year (Office), Free to \$12/month, \$25/month	Custom pricing	Custom pricing	Custom pricing
Launch Year	n/a	1983 - 2006	1990 - 2005	1969 - 2000	1900 - 2001
ChatGPT ranking	1	2	3.5	4	5

Source: The table draws upon various sources of information including desk research, and websites of companies like Microsoft, Google, Salesforce, SAP, Oracle, Zebra Tech, IBM, SwissLog, Dematic, and Honeywell Integrated. The prompt for the CHATGPT ranking is available in the appendix.

A.2.1 Comparison between experts' and ChatGPT's sophistication rankings

We validate the industry experts' technology sophistication rankings using AI-powered large language models. To start, we prepared files with the list of business functions and associated technologies in the grid, keeping the way they are described in the FAT survey. We generate separate files for GBFs and each specific sector functions. We then uploaded these files and asked ChatGPT to rank the sophistication of these technologies, providing the following prompts:

1. Based on the survey questions from the document, please create a report ranking the level of technological sophistication for each technology within business function on a scale of 1 to 5, where 1 represents the most basic technology and 5 represents the most sophisticated technology. You can use decimal points. Generate a report file with this information. Provide the data in an Excel sheet.

2. Please expand the previous exercise by providing the rank of technology sophistication for each of these definitions: 1) Functionality: The breadth and depth of features and capabilities that technology offers to perform various tasks and processes within a business function. Higher functionality indicates the ability to handle more complex tasks associated with the business function on a larger scale, faster, with more accuracy and reliability. 2) Integration: The ability of a technology to connect and interact seamlessly with other systems, platforms, or technologies within the business ecosystem. Higher integration means the technology can easily exchange data and coordinate processes with other systems. 3) Automation: The extent to which a technology can perform tasks automatically without human intervention. Higher levels of automation imply that the technology can execute processes, make decisions, and generate outcomes on its own.

Tables A.1 - A.13 summarize the main results from prompt 1. Figures A.12-A.16 show the strong positive association between ChatGPT-specific rankings of technology sophistication for functionality, integration, and automation with industry experts' rankings, from prompt 2. The rankings provided by ChatGPT are strongly correlated with our technology sophistication ranking, which is defined by human experts. The overall correlation across all functions and various definitions is above 90%. The results are similar across all business functions.

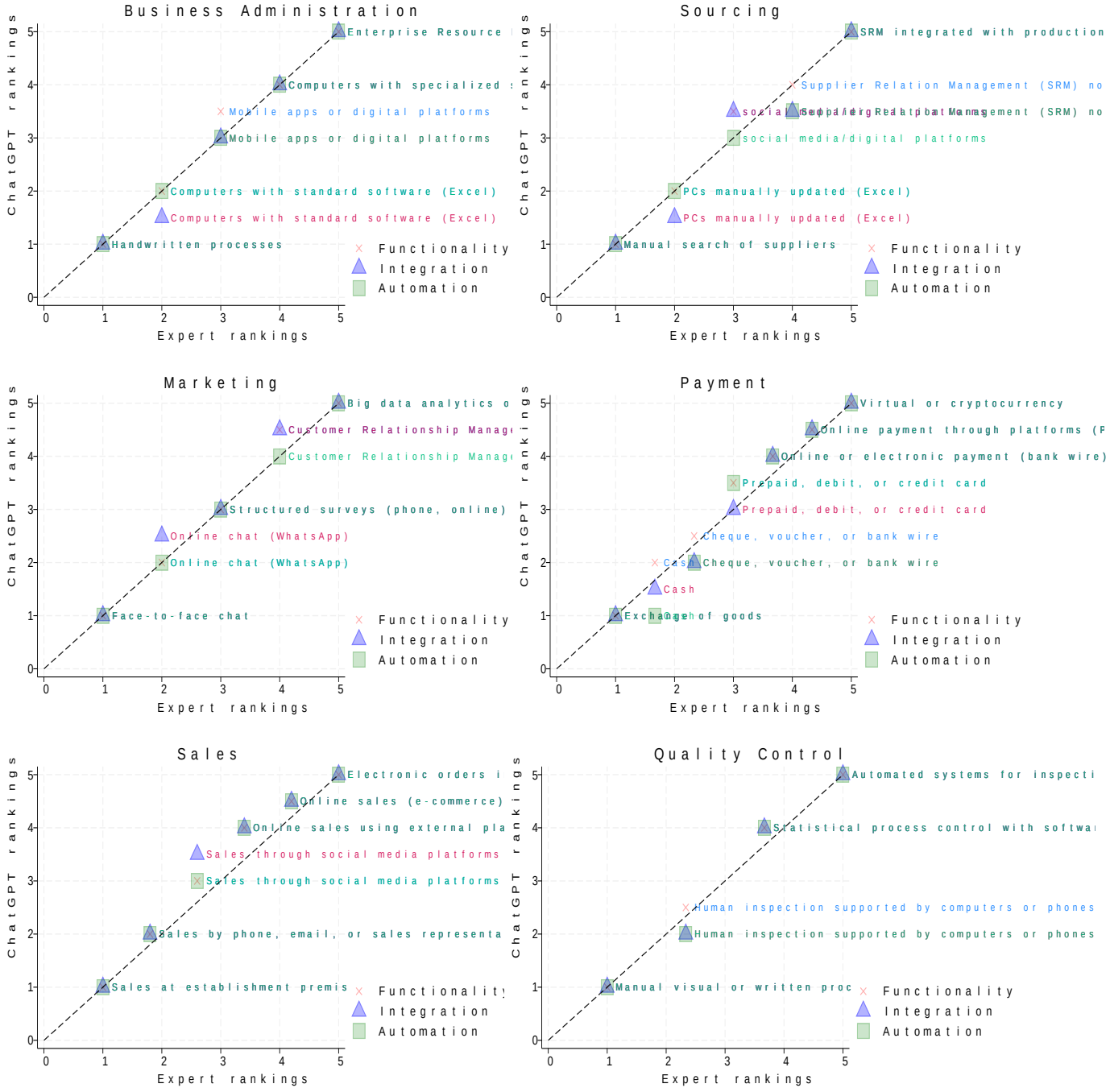


Figure A.12: Comparison between expert's versus ChatGPT's in General Business Functions

Note: This figure compares the experts' rankings of technology sophistication (horizontal axis) with ChatGPT's rankings across the dimensions of functionality, integration, and automation (vertical axis).

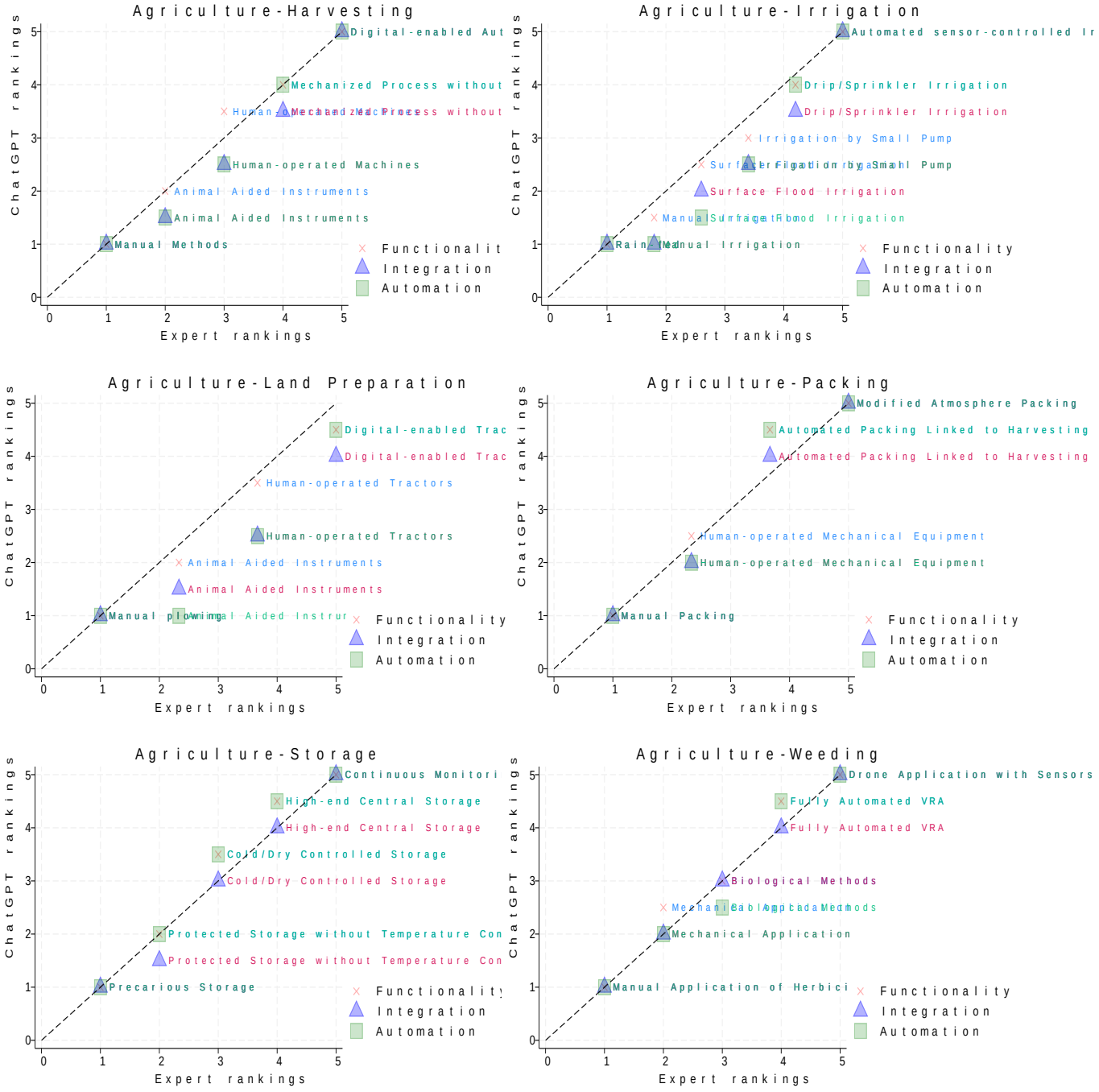


Figure A.13: Comparison between expert's versus ChatGPT's in Agriculture

Note: This figure compares the experts' ranking of technology sophistication (horizontal axis) with ChatGPT's rankings across the dimensions of functionality, integration" "and automation (vertical axis).

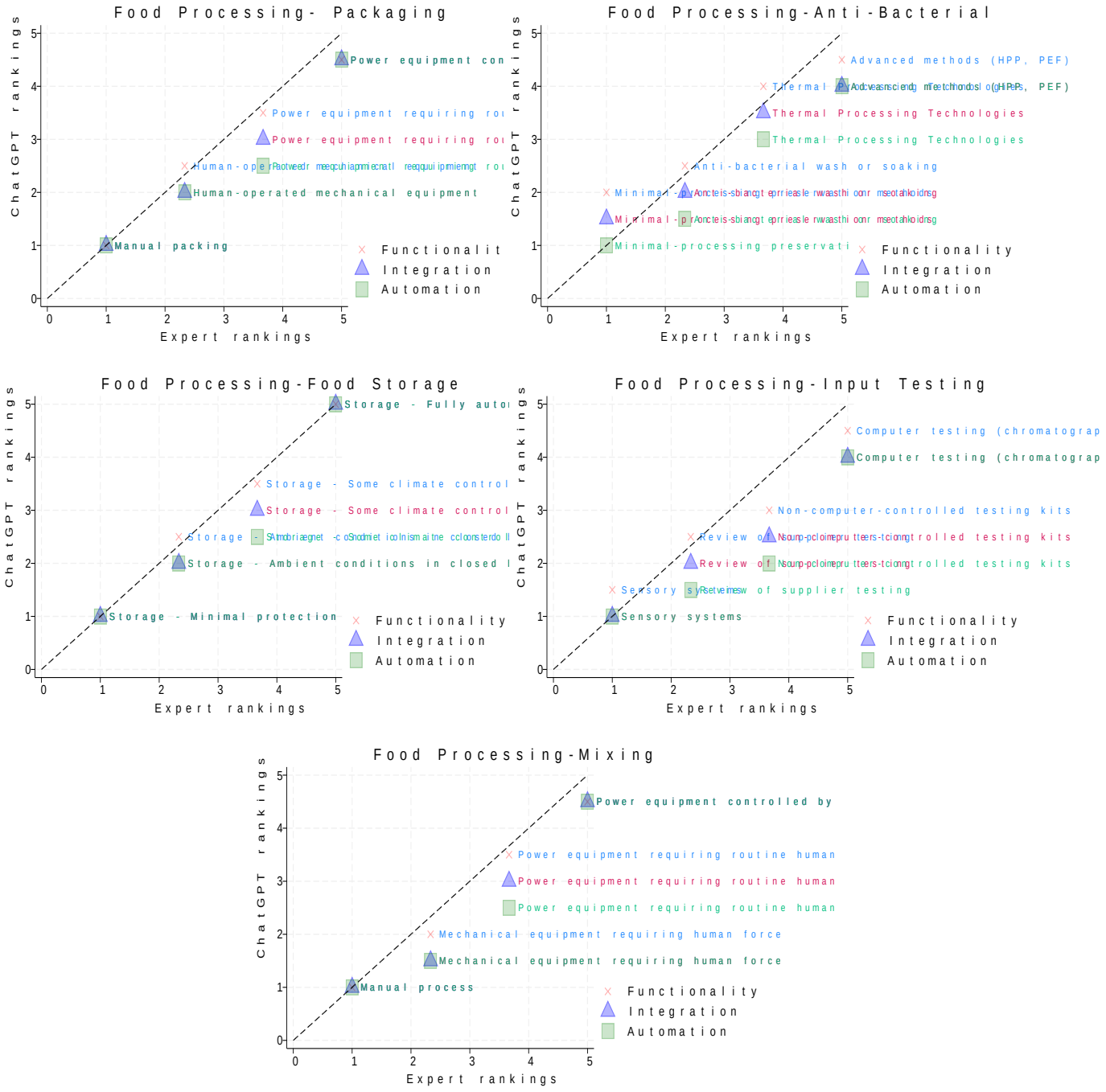


Figure A.14: Comparison between expert's versus ChatGPT's in Food Processing

Note: The figure compares the experts' ranking of technology sophistication (horizontal axis) with ChatGPT's rankings across the dimensions of functionality, integration" "and automation (vertical axis).

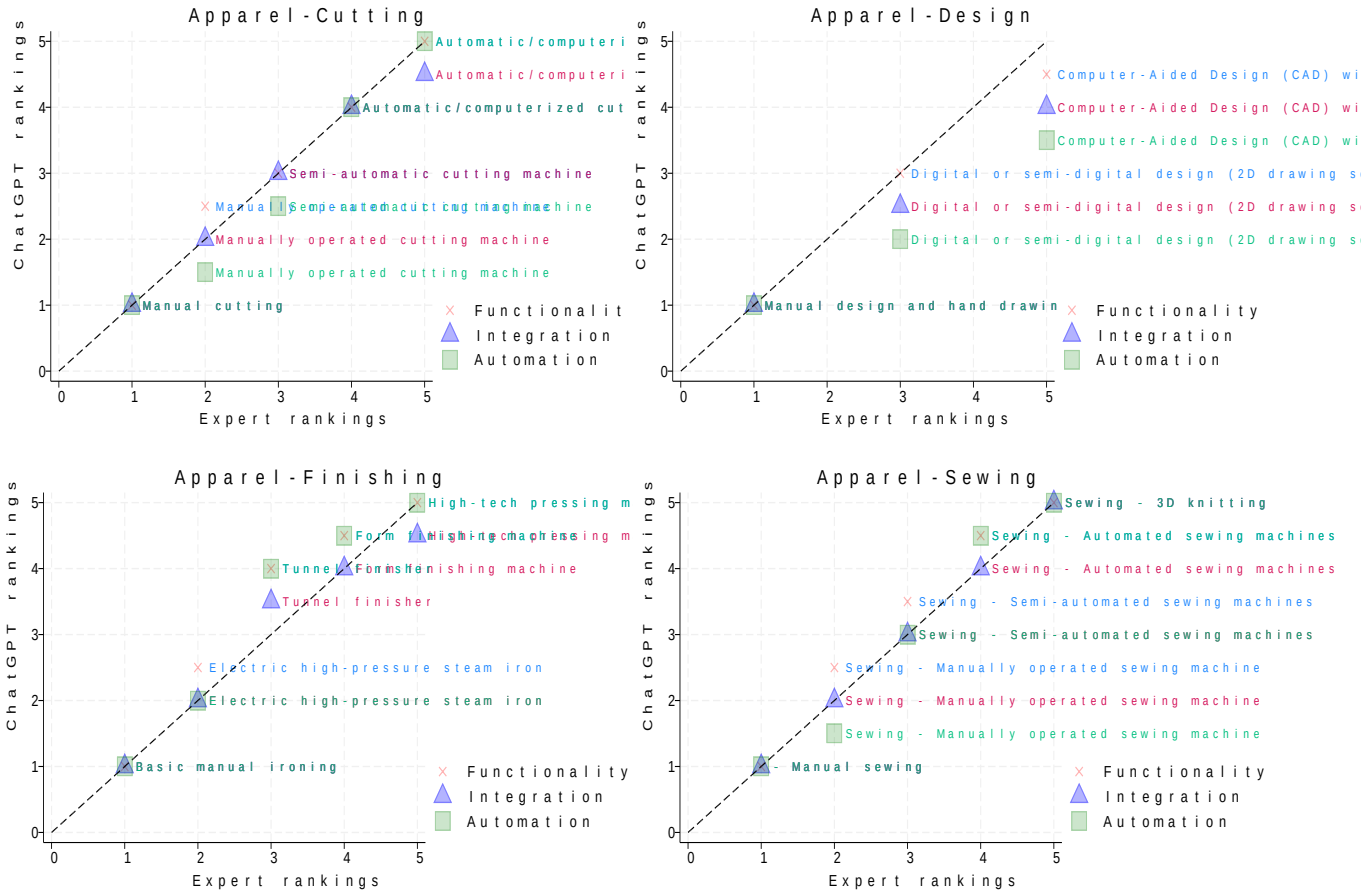


Figure A.15: Comparison between expert's versus ChatGPT's in Apparel

Note: The figure compares the experts' ranking of technology sophistication (horizontal axis) with ChatGPT's rankings across the dimensions of functionality, integration" "and automation (vertical axis).

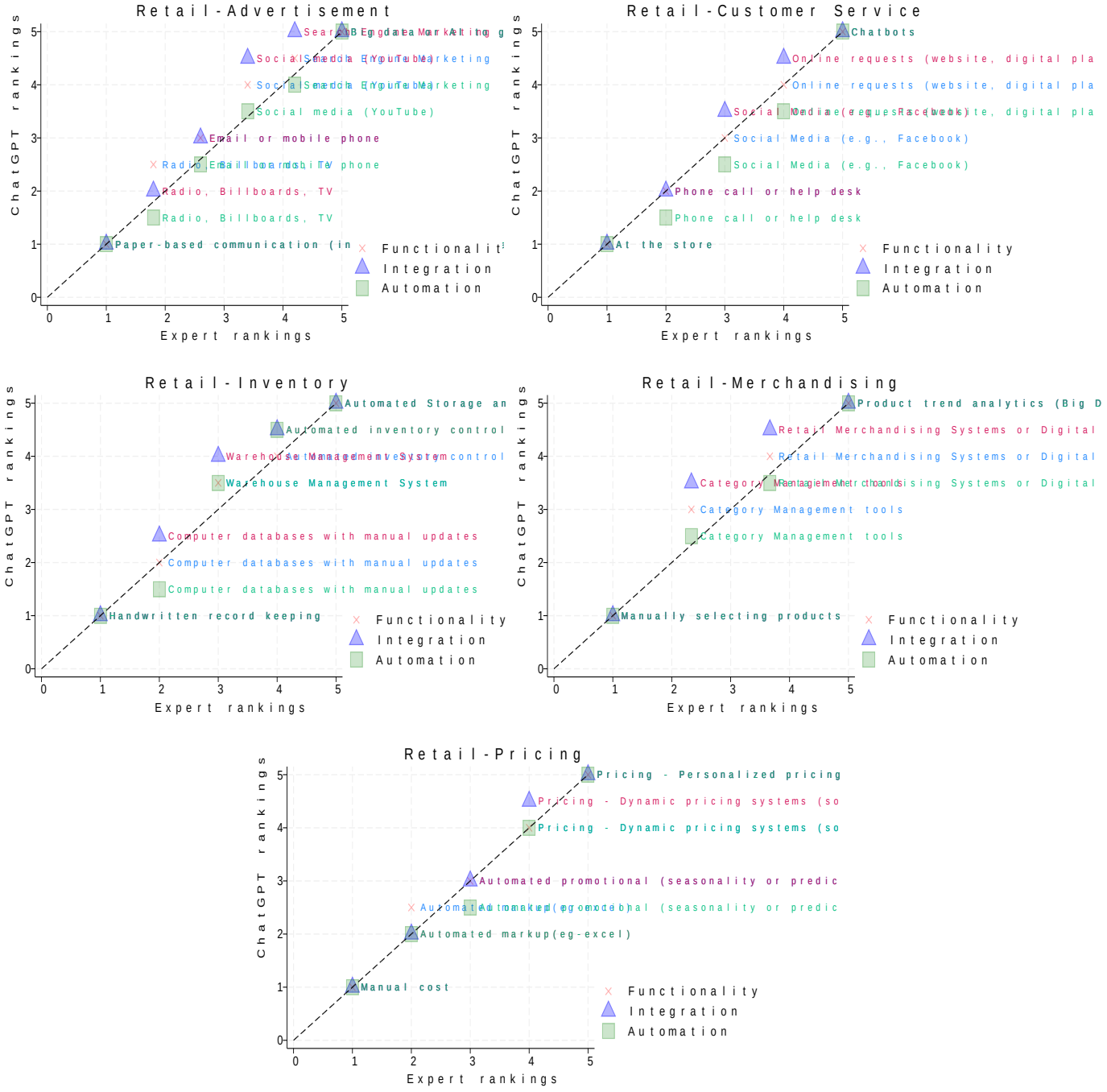


Figure A.16: Comparison between expert's versus ChatGPT's in Retail

Note: The figure compares the experts' ranking of technology sophistication (horizontal axis) with ChatGPT's rankings across the dimensions of functionality, integration" "and automation (vertical axis).

A.3 Calculation of Relative Productivity of Technologies to construct Q-cardinalization Measures

In this section, we discuss the methodology we follow to calculate the relative productivity of the technologies in the grid for the construction of Q-cardinalizations.

The methodology consists of three steps. First, identify a representative and significant task within the business function. Second, define productivity measures appropriate for that task and for the technologies used in the business function; these measures should capture time, effectiveness, and/or accuracy of task completion. Third, compute technology productivity for each business function using four types of sources: (i) peer-reviewed academic research, (ii) structured field interviews with experts who were not involved in the grid assembly, (iii) industry studies and (iv) commercial information from technology providers.

We prioritize the use of academic peer-reviewed journals. Thus, whenever we find rigorous studies published in peer-reviewed journals assessing the productivity gains from a specific technology, we use these estimates as a reference. Yet, these are often not available and in those cases we try to reach out to industry experts. These are typically either providers of the technologies or users that are very familiar with various technologies in one or several business functions of the sectoral or general business functions grid.

For example, in agriculture, we talked to farmers managing properties of different sizes in Brazil, along with an agronomist engineer working as a consultant on the adoption of technologies for a large cooperative in Brazil, and a representative of John Deere equipment. In banking, we gathered information from managers and back-office experts from five medium-sized banks in India. In business administration, we interviewed two professionals in Brazil, one with experience in human resources and the other in general business administration, and we also gathered information from the managers of an electrical equipment company in Philippines who have had experience with the different technologies covered by the grid in business administration. This same company also provided information on the relative productivity of technologies in two other general business functions: production planning and quality control. When we have multiple experts providing information on a given business function, we compute the simple average of the implied Q-productivity ($Q_{f,\tau}$) provided by all experts.

When we do not have access to academic publications or experts, we have used industry studies and commercial information from technology providers to calculate the productivity of the technologies in conducting the representative task in the business function.

Table A.14 provides a detailed characterization of the type of sources used for each technology in each business function, the task and the productivity measure. Overall, we

have collected information to construct Q-cardinalizations in 18 of the 63 business functions. These include 3 out of 7 general business functions; 4 out of 6 functions in agriculture, 4 out of 5 in retail and wholesale; 4 out of 5 in banking; 2 in healthcare and 1 in apparel.

We have selected these functions largely because of availability of information about the relative productivity for the technologies in the grid. Despite the soundness of the methodology and the significant effort in collecting the data and calculating the Q-productivities, it is important to acknowledge several complexities that such an exercise involves.

First, as discussed in section 2.3, more sophisticated technologies often embody new functionalities that sometimes allow establishments to perform tasks that were not feasible with less sophisticated technologies. Our methodology defines a common, relevant task that can be performed with all the technologies in the function; therefore it does not capture gains from sophisticated technologies that arise from enabling entirely new tasks. We partly address this limitation by defining tasks broadly enough that the new functionalities of sophisticated technologies can still affect the productivity metric. For example, specialized software with automated reminders and confirmation used to scheduling medical appointments not only reduces the time to schedule them but also reduces the no-show rate and increases the likelihood of successfully scheduling the appointment relative to phone calls. By defining the task as "successfully scheduling appointments" and the metric as the "time of administrative staff and client required to successfully schedule an appointment" we are capturing the enhanced functionalities of the sophisticated technologies.

Second, the relative productivity of sophisticated technologies may depend on the scale of operations of the establishment. For example, if the time it takes to conduct a task increases linearly with scale for unsophisticated technologies but it increases less than linearly for sophisticated ones, the relative productivity of sophisticated vs. unsophisticated technologies will increase with scale. We have avoided the complexity that scale brings to the measurement of relative productivities by fixing the scale of establishments across the different computations. Specifically, since the median establishment in FAT has 9 workers, we have framed the calculations of productivities in the context of establishments with a size of 10 workers.

Third, the relative productivity of technologies may differ across countries or establishments if the relative effectiveness of sophisticated vs. unsophisticated technologies in performing designated tasks is influenced by non-technological factors. In such cases, users or experts may perceive varying levels of (relative) productivity depending on the contextual factor profile of their country or setting. We have dealt with this potential challenge by consulting experts from middle-income countries (Brazil, Philippines, India).

Given these caveats, the resulting estimates of Q-productivities should be interpreted

with caution. The objective of the exercise is not to produce definitive measures of relative productivity, but rather to systematically collect data that enables the construction of reasonable Q-productivity estimates as a foundation for Q-cardinalizations. Based on these cardinalizations, we assess the robustness of the baseline establishment-level technology sophistication measures –MAX_j and $MOST_j$– and examine how their patterns respond to alternative cardinalization approaches, including those based on z-scores and Q-productivity metrics.

The rest of the section is organized as follows. Table A.14 presents the business functions for which we conduct the Q-cardinalizations and, for each function, the relevant task, the productivity measure and the type of sources used to obtain the required information to compute it for each technology in the grid. Tables A.16-A.20 provide information on the time it takes to perform each relevant task with each technology, the Q-productivities ($Q_{f,\tau}$) and the type of sources used to calculate them. Section A.3.1 contains the details about those calculations and the references used to compute them.

Table A.14: Business Functions with Independent Measures of Relative Productivity

Sector	**Business Function**	**Task**	$Q_{f,\tau}$	**Type of Sources**
GBF	Business Administration	Managing payroll and finance report for 10 workers	1/Time to manage monthly payroll	II,III
GBF	Production Planning	Forecasting	1/Time to manage production planning	II
GBF	Quality control	Inspection of production batch and defect reduction	1/Time to conduct quality control	II
Agriculture	Land Preparation	Prepare for cultivation 160 hectares of land	Hectare/hours*person	II, IV
	Harvesting	Harvest a 160 hectare field	Hectare/hours*person	I,II, III, IV
	Weeding and pest control	Spraying of a 160 hectare field	Hectare/hours*person	I,II, IV
	Storage	Preserve crop once stored	Expected time that crop can be preserved in storage	I,II
Retail	Customer service	Providing service to 10 customers	1/time to provide customer service to one client	II
	Pricing	Update prices for 1000 items	1/time to update prices	II
	Mechandising	Choose 1000 products to display	1/time to select products to display	II
	Inventory	Record and maintain inventory of 1000 products	1/time to maintain and record inventory of goods	I,II
Apparel	Design	Design 10 dresses	1/time to design	I,III
Healthcare	Appointments	Effectively schedule 1 doctor appointment	(Prob of scheduling Appointment *(1-Prob no-show) / (Patient Time+Admin Time)	I, III
	Drug administration	Delivering drugs to patients, avoiding serious adverse drug events (ADEs)	(1-% of error rate in drug administration)	I
Banking	Customer Service	Processing 50 deposit/withdrawal transactions	1/staff time	II
	Loan application	Processing 50 loan applications	1/staff time	II
	Loan approval	Approving/Denying 50 loan applications	1/staff time	II
	Operations	Recording banking transactions (25 deposit/withdrawal + 25 loan applications)	1/staff time	II

Note: Type of sources are coded as follows: Academic papers (I), experts (II), industry reports (III), company webpage (IV). Experts refer to workers or managers with experience in using the technology to perform the task or technology providers. Section A.3 of the Appendix provides details and estimates for each technology in the business function.

Table A.15: Relative productivity in Business Administration - GBF

Technology	**Time to perform the task**	**Measures**	$Q_{f,\tau}$	**Baseline ranking**	**Type of Sources**
Business Administration Task: Managing payroll and finance report					
Handwritten Processes	15	Hours	1.00	1	II
Computers with Standard Software	9	Hours	1.51	2	II
Mobile Apps or Digital Platforms	6.6	Hours	1.82	3	II
Specialized Software	2.6	Hours	2.76	4	II
Enterprise Resource Planning (ERP)	1.2	Hours	3.56	5	II, III
Production planning Task: Demand forecast report					
Handwritten Processes	10.4	Hours	1.00	1	II
Computers with Standard Software	6.8	Hours	1.42	2	II
Mobile Apps or Digital Platforms	6.2	Hours	1.52	3	II
Specialized Software	4.8	Hours	1.77	4	II
Enterprise Resource Planning (ERP)	2.5	Hours	2.43	5	II
Business Administration Task: Managing payroll					
Manual, visual, or written processes	16.8	Hours	1.00	1	II
Human inspection with the support of computers or phones	8.8	Hours	1.65	2	II
Statistical process control	1.6	Hours	3.35	3	II
Automated systems for inspection	3.2	Hours	2.66	4	II

Note: Type of sources codes are as follows: Acamedic papers (I), experts (II), industry reports (III), company webpage (IV).

Table A.16: Relative productivity in Agriculture

Business Function/Technology	Time to perform the task	Measures $Q_{f,\tau}$		Baseline ranking	Type of Sources
Land Preparation **Typical task: Prepare for cultivation 160 hectare field by 2 workers**					
Manual plowing with simple tools	2400	Days	1.00	1	II
Animal Aided Instruments (ploughs)	640	Days	2.32	2.3	II
Tractors or other manually operated equipment	9.5	Days	6.53	3.7	II, III
Tractors with digital technologies	8.2	Days	6.68	5	II, III
Weeding and Pest Control **Typical task: Spraying of a 160 hectare field by 2 workers**					
Manual application of herbicide/pesticide	160.0	Days	1.00	1	II
Mechanical application of herbicide/pesticide	1.6	Days	5.61	2	II
Biological methods	4.8	Days	4.51	3	I, II
Variable Rate Application (VRA) tools	0.36	Days	7.10	4	II
Drone Application with remote sensing	4.00	Days	4.69	5	II
Harvesting, Training, Pruning **Typical task: Harvesting 160 hectare field by 5 workers**					
Manual harvesting	1220	Days	1.00	1	I, II
Animal Aided Instruments	560	Days	1.78	2	I, II
Human-operated machines	60	Days	4.01	3	I, II
Mechanized process without digital tech	16	Days	5.33	4	I, II, III, IV
Automated process with digital tech	12	Days	5.62	5	I, II, III, IV
Storage (Post-Harvesting) **Typical task : Preserve crop once stored**					
Precarious facility	0.5	Months	1.00	1	II
Basic storage without temperature control	6	Months	3.48	2	II
Cold storage facility	12	Months	4.18	3	II
High-end central storage with automation	24	Months	4.87	4	I, II
Continuous monitoring with sensors	36	Months	5.28	5	I, II

Note: Type of sources codes are as follows: Acamedic papers (I), experts (II), industry reports (III), company webpage (IV).

Table A.17: Relative productivity in Retail

Business Function/Technology	Time to perform the task	Measures $Q_{f,\tau}$		Baseline ranking	Type of Sources
Customer Service **Typical Task: Serve 10 customers**					
At the Store	3	Hours	1.0	1	II
Phone call or call Help Desk	2	Hours	1.4	2	II
Social Media	2	Hours	1.4	3	II
Online requests (website or app)	0.83	Hours	2.3	4	II
Chatbots	0.5	Hours	2.8	5	II
Pricing **Typical Task: Update prices for 1000 items**					
Manual Cost	8.3	Hours	1.0	1	II
Automated markup (excel or similar)	4.5	Hours	1.6	2	II
Automated promotional pricing	0.25	Hours	4.5	3	II
Dynamic pricing systems	0.09	Hours	5.5	4	II
Personalized pricing with predictive analytics	0.05	Hours	6.1	5	II
Merchandising **Typical Task: Choose 1000 items for display**					
Manually selecting products	8.3	Hours	1.0	1	II
Category Management tools	0.33	Hours	4.2	2.3	II
Retail Merchandising Systems or Digital Merchandising	0.08	Hours	5.6	3.7	II
Product trend analytics	0.05	Hours	6.1	5	II
Inventory **Typical Task: Record inventory for 1000 SKUs**					
Handwritten record keeping	24	Hours	1.0	1	I, II
Computer databases with manual updates	18	Hours	1.3	2	I, II
Warehouse Management System with specialized software	12	Hours	1.7	3	I, II
Automated inventory control (CAO), VMI, RFID	0.08	Hours	6.7	4	I, II
Automated Storage and Retrieval systems (AS/RS)	0.08	Hours	6.7	5	I, II

Note: Type of sources codes are as follows: Acamedic papers (I), experts (II), industry reports (III), company webpage (IV).

Table A.18: Relative productivity in Banking

Business Function/Technology	Time to perform the task	Measures	$Q_{f,\tau}$	Baseline ranking	Type of Sources
Customer Services (Checking & Savings Accounts) **Typical task: Processing 50 transactions**					
Teller (Face-to-face)	4.2	Hours	1.0	1	II
ATM Machines	1.4	Hours	3.2	2.3	II
Online Banking via Company Website	1.4	Hours	3.2	3.7	II
Mobile Banking	1.4	Hours	3.2	5	II
Loan Applications **Typical task: Processing 50 loan applications**					
Loan Officer, Paper-Based, In-Person	33.3	Hours	1.0	1	II
Mobile/Phone Application Plus Paper-Based Submission	20.8	Hours	4.9	3	II
Internet/Mobile Phone Applications (Fully Digital Process)	8.3	Hours	5.4	5	II
Credit Approval Process **Typical task: Approving 50 loan applications**					
Analyst Decision Based on Paper Documents	500.0	Hours	1.0	1	II
Analyst Decision Based on Digital Information	16.7	Hours	8.7	2.3	II
Automated Decision Mechanisms Using Specialized Software	0.8	Hours	9.2	3.7	II
Credit Appraisal Algorithm Using AI or Big Data Analytics	0.2	Hours	9.4	5	II
Operational Support Technologies **Typical task: Recording 50 financial transactions**					
Purely Rely on Writing Records from Employees	180	Hours	1.0	1	II
Digital Accounting & Document Management (PC-Based)	3.3	Hours	4.3	3	II
Digital Network (Centralized System Across Branches)	2.2	Hours	5.4	5	II

Note: Type of source codes are as follows: Academic papers (I), experts (II), industry reports (III), company webpage (IV).

Table A.19: Relative productivity in Apparel

Business Function/Technology	Time to perform the task	Measures $Q_{f,\tau}$		Baseline ranking	Type of Sources
Design **Typical task: Creating 10 clothing designs**					
Manual design and hand drawing	14,067	Minutes	1.00	1	I, III
Digital or semi-digital design using specialized 2D drawing software	10,000 – 5000	Minutes	1.63	3	I, III
Computer Aided Design (CAD), 3D design, virtual prototyping	2,748	Minutes	2.63	5	I, III

Note: Types of source codes are as follows: Academic papers (I), experts (II), industry reports (III), company webpage (IV).

Table A.20: Relative productivity in Health

Technology	Time to perform the task	Measures	$Q_{f,\tau}$	Baseline ranking	Type of Sources
Scheduling Appointments **Typical task: Scheduling 10 appointments manually**					
Personal visit and paper	23	Minutes per effective appointment	1.0	1	I,III
Phone call, SMS, or Email	22	Minutes per effective appointment	1.0	2.3	I,III
Spec. software or app WITHOUT automated reminders	4.4	Minutes per effective appointment	2.9	3.7	I,III
Spec. software or app WITH automated reminders and confirmation	5.2	Minutes per effective appointment	2.7	5	I,III
Medication Management and Administration					
Handwritten monitoring	0.94	Probability of delivering correct medication	1.0	1	I
Barcode or electronic identification	0.95	Probability of delivering correct medication	1.0	5	I

Note (1): Minutes per effective appointment is defined as $\frac{\text{Patient Time+Admin Time}}{\text{Prob of scheduling Appointment *(1-Prob no-show)}}$.
Note (2): Types of source codes are as follows: Academic papers (I), experts (II), industry reports (III), and company webpage (IV).

A.3.1 Details about the Calculations of $Q_{f,\tau}$

General Business Functions

We consulted three experts, two from Brazil and one from the Philippines, to provide these estimates. The first expert from Brazil has worked in HR departments of companies of a wide range of sizes (small, medium, and large) over the last twenty years. Currently, he is in charge of managing payroll for employees of a transportation company with about 1000 workers. The second expert is an accountant who has been working with managing ERP system in medium-sized companies. While the first expert provided estimates for all technologies, the second provided detailed information about the process with an estimate for two technologies (standard software and ERP). Based on this information, we had a follow-up discussion with the first expert to build a consensus around the estimated time to manage monthly payroll in a 10-worker company.

The third consultant was the manager of an electrical equipment company in the Philippines with 500 workers, including 50 in administration. They produce wire harnesses and assemblies for power supply and electrical components, electrical appliances, electronic equipment, and automotive. The manager provided information for the estimated time to conduct tasks related to three business functions: i) Managing payroll and financial reports; ii) Forecasting demand (production planning); and iii) Quality control inspections. Their estimates refer to the time that it would take to conduct these tasks in their company with 10 workers dedicated to the task.

For each technology τ in business administration, we computed the average of the implied $Q_{f,\tau}$ from the estimated productivities across all the experts from Brazil and the company in the Philippines. For production planning and quality control, we used the estimates provided by the company in the Philippines.

Business Function: Business Administration

- Tasks: Managing payroll and generating finance reports
- Productivity measure: Hours to complete the task.

Calculations:

- All estimates are based on the average $Q_{f,\tau}$ estimates from experts from Brazil and the Philippines.

Complementary evidence: Spathis and Constantinides (2024) show that reducing the time for closing annual accounts and issuing financial reports, along with further integration with accounting applications, are among the most relevant perceived impacts reported by ERP adopters.

Reference: Spathis, Charalambos, and Sylvia Constantinides. (2004) "Enterprise resource planning systems' impact on accounting processes." Business Process Management Journal 10.2: 234-247.

Business Function: Business Planning

- Tasks: Forecasting
- Productivity measure: Hours to complete the task.

Calculations:

- All estimates are based on information provided by experts from the Philippines.

Business Function: Quality control

- Tasks: Inspection
- Productivity measure: Hours to complete the task.

Calculations:

- All estimates are based on information provided by experts from the Philippines.

Agriculture

We consulted with farmers managing properties of different sizes in Brazil, along with an agronomist engineer working as a consultant on the adoption of technologies for a large cooperative in Brazil, and a representative of John Deere equipment in the same cooperative.

Our reference point was a farm with a 162-hectare field that produces soybeans, corn, and wheat. We obtained information from the owner, who directly manages the use of these technologies to perform these business functions, the agronomist engineer, and the representative of John Deere equipment, familiar with the farm and the use of the technologies in it. For most of these tasks, the reference farm adopted the two most sophisticated technologies (e.g., mechanized process with and without digital technologies for harvesting). For these

technologies, the owner provided the initial estimates. We then independently collected the information from the agronomist engineer and the representative of John Deere equipment, who validated the information. To ascertain the productivity of less sophisticated technologies in the grid, we consulted with another farmer managing a smaller property and with longer professional experience with more basic technologies. Additionally, we also documented the productivity of less sophisticated technologies using academic articles that estimate them using historic data, as described below.

Agriculture Business Function: Land preparation

- Task: Prepare the land for the cultivation of a 160-hectare field.
- Productivity measure: Number of days to complete the task by 2 workers.

Calculations:

- Manual plowing with a simple tool. An expert (small farm) estimated 15 days of preparation necessary for 1 hectare. We use the lower bound (15 days) times 160 hectares.
- Animal Aided Instruments. An expert (small farm) estimated 3 days of preparation for 1 hectare. We use these estimates times 160 hectares.
- Tractors or other manually operated equipment: Estimates from experts (farmer, consultant, and technology provider) for the reference farm.
- Tractors with digital technologies. Estimates from experts (farmer, consultant, and technology provider) for the reference farm.

Agriculture Business Function: Wedding and Pest Control

- Task: Wedding and Pest Control treatment in a 160-hectare field by 2 workers.
- Productivity measure: Number of days to complete the task.

Calculations:

- Manual application of herbicide/pesticide. An expert (small farm) estimated 1 day of spray for 1 hectare. We multiplied it by 160 hectares.

- Mechanical application of herbicide/pesticide. Estimates from experts (farmer, consultant, and technology provider) for the reference farm.
- Biological methods. It is assumed that it takes 3 times longer than the mechanical application of herbicide/pesticide. Pretty and Bharucha (2015) suggest that for many farmers biological methods is still considered time-consuming.
- Variable Rate Application (VRA) tools. Estimates from experts (farmer, consultant, and technology provider) for the reference farm.
- Drone Application with remote. Estimates from experts (consultant and technology provider) for the reference farm. The experts explained that, despite being very sophisticated, the use of drones currently would take longer than mechanical application or VRA. The main reason to adopt this technology would be to avoid direct contact with the plant.

References:

Pretty, Jules, and Zareen Pervez Bharucha. (2015) "Integrated pest management for sustainable intensification of agriculture in Asia and Africa." Insects 6.1: 152-182.

Business Function: Harvesting, Training, Pruning

- Task: Harvesting soybeans in a 160-hectare field.
- Productivity measure: Number of days to complete the task by 5 workers.

Calculations:

- Manual harvesting. Estimates based on information provided by experts in Brazil. Musoni et. al. (2013) estimate 198 man-hours per hectare for manually harvesting soybeans in Zimbabwe. Converting it to our reference farm and assuming between 5-6 hours of work per day,[41] it would take about 1,056-1267 days to complete the work.
- Animal Aided instruments. Musoni et. al. (2013) provide equivalent measures for animal-aided, which is equivalent to 86 man-hours per hectare. We use the ratio between the two measures (manual/aided instruments) that suggests a reduction of time by about 56% between manual and aided instruments.
- Human-operated machines. Estimates provided by experts in Brazil.

[41] Musoni et. al. (2013) assume a maximum of 6 hours of work a day,

- Mechanized processes without digital tech were provided by experts in Brazil.
- Automated processes with digital tech were provided by the experts at the reference farm in Brazil.

Complementary evidence:

Our estimates are broadly aligned with additional evidence from academic literature and company sources. Hossain et. al. (2015) shows that the time saving by combine harvesters used for rice and wheat in Bangladesh over manual methods was 97.5%.[42] These estimates are broadly aligned with other references provided by Hassan et. al. (2020). Our estimates suggest time savings of about 98% and 99% by moving from manual harvesting to combined harvesters without or with digital technology, respectively. Additional evidence for the US suggests large productivity gains with mechanization in harvesting. Hecht and Vice (1981) attributed these gains to "the almost complete conversion from horses and mules to tractors, trucks, and other forms of mechanical power and associated machines is the main reason for the big drop."

A document from John Deere describing the potential gains from using the frontier technology – a specific tractor that includes an automatic pitot with the *AutoTrac* technology – suggests potential savings up to 14% in productivity gains. Our estimates suggest gains of 25% in the time savings comparing mechanized processes with and without digital technology.

References:

Hossain, M. A., Hoque, M. A., Wohab, M. A., Miah, M. M., Hassan, M. S. (2015). Technical and economic performance of combined harvester in farmers field. Bangladesh Journal of Agricultural Research, 40(2), 291-304.

Hasan, K., Tanaka, T.S., Alam, M., Ali, R. and Saha, C.K., 2020. Impact of modern rice harvesting practices over traditional ones. Reviews in Agricultural Science, 8, pp.89-108

Hecht, R. and Vice, R. (1981) Labor Used For Field Crops. Production Economics Research Branch. Agricultural Research Services, United States.

Johnston P. and Myers, K. (1931) Harvesting the corn crop in Illinois. University of Illinois. Agricultural Experiment Station. Bulletin, 373.

Musoni, Special, M. Raymond, and M. Leonard Nazare. (2013) "Mechanisation Of Soya Bean Harvesting For Small And Medium Scale Farmers In Zimbabwe." IOSR Journal Of Agriculture And Veterinary Science (IOSR-JAVS) 2.3: 51-53.

Agriculture Business Function: Storage

[42]Primary data were collected from 30 adopter and 30 non-adopter farmers from each district of Bogra, Rangpur, Dinajpur, and Thakurgaon through direct interviewing during 2012-13. Information was also collected from different combine harvester traders available in Bangladesh.

- Task: Preserve crop once stored.
- Productivity measure: Number of months stored, keeping the product quality.

Calculations:

- Precarious facility. This is a very vulnerable position. In the case of soybeans or corn, they will lose quality features if exposed to the first rain. We use 2 weeks as a reference point, provided by experts in the region of the reference farm. However, there is a large variation in precipitation over the year and across regions.
- Basic storage without temperature control. Estimates from experts (farmer, consultant, and technology provider) for the reference farm.
- Cold storage facility. Estimates from experts (farmer, consultant, and technology provider) for the reference farm. Estimates from experts (farmer, consultant, and technology provider) for the reference farm.
- High-end central storage with automation. Estimates from experts (farmer, consultant, and technology provider) for the reference farm.

Our estimates are broadly consistent with the literature, suggesting that "the suitable temperature, humidity, and gas composition of grain storage environments will cause the growth and reproduction of pests and fungi" (Zhao et. al. 2023), with references describing that adoption of cold storage (5 °C) to preserve rice grains achieved good storage efficacy for a storage period of up to 24 months.

References:

Zhao, Y., Lv, H., Li, Y. (2023). Grain storage: Theory, technology and equipment. Foods, 12(20), 3792.

Retail

For Retail, we collected information from a manager of a grocery retail company with 100 workers in Brazil. This manager is about 50 years old and has 30 years of professional experience with various sizes of grocery stores — from mom-and-pop shops to large chains. In addition, he grew up in a family that owned a small grocery store and was exposed to various levels of technology.

We followed our standard procedure by sharing our technology grid for retail and asking him to define a typical relevant task for his businesses, propose adequate measures, and estimate the time to perform the task. We have an initial call describing the request and explaining the grid. Once he shared the information, we had a follow-up call to discuss the measures and obtain their specific explanation.

To provide the estimates, the manager ran small pilots of the task with workers who were in charge of conducting these activities.

Banking

For Banking we collected information from managers and IT directors from 5 small and medium-sized banks in India. A banking expert with 25 years of experience trained by us in the FAT survey and the banking grid interviewed managers and IT experts from 5 small and medium-sized Indian banks who provided their independent estimates on the time it takes to conduct the representative task in each business function with each technology. They also provided detailed explanations on the sub-tasks required to complete each representative task with each technology and approximate times involved. We checked the consistency of the total estimates with the estimates to complete the sub-tasks. The reported times are the average across the estimates from the 5 banks. Though each bank interacted independently with the banking expert, their individual estimates are very consistent.

Business Function: Customer Services (Checking Savings Accounts)

- Task: Processing 50 transactions in person
- Productivity measure: Inverse of the time it takes to conduct the task.

Business Function: Loan Applications

- Task: Processing 50 loan applications
- Productivity measure: Inverse of the time it takes to conduct the task.

Business Function: Credit Approval

- Task: Evaluating and approving (if pertinent) 50 loan applications
- Productivity measure: Inverse of the time it takes to conduct the task.

Business Function: Operational Support Technologies

- Task: Recording 25 deposit and withdrawal transactions and 25 loan loan application/approval/rejection transactions
- Productivity measure: Inverse of the time it takes to conduct the task.

Apparel

Apparel Business Function: Design

- Task: Creating 10 clothing designs
- Productivity measure: Minutes to complete the task.

Calculations:

- Manual design and hand drawing. Kılıç (2019) shows that for several tasks related to design, including modeling, grading, and cloth-spreading, the time required to perform the process manually is statistically significantly longer than the one required for completing the same task on CAD systems. The estimated median time is 14,067 minutes.
- Computer Aided Design (CAD), 3D design, virtual prototyping. Kılıç (2019) estimates that the median time by CAD is 2,748. The evaluation of total process time suggests that the time required for completing the processes manually is more than 5 times greater than that required for CAD systems.
- Digital or semi-digital design using specialized 2D drawing software. Khomariah et. al (2025) state that "One of the most significant innovations that has impacted the fashion industry is the use of 3D software in the design process." By comparing CLO 3D software to 2D software, the authors argue that 3D technologies allow for faster prototyping, which means that designers can create more designs in less time. Kuzmichev and Yan (2022) suggest that brands using 3D digital garment design and development processes record up to a 50%–75% reduction in time spent on product development. Applying these reduction percentages to the time to design 10 dresses using 3D CAD technologies provided by Kılıç (2019), we infer an approximate time to produce ten designs using 2D of between 5,000-10,000.

References:

Kılıç, A. (2019). Comparison of CAD and manual system efficiency in pre-production preparation process. Textile and Apparel, 29(1), 73-84.

Kuzmichev, V., Yan, J. (2022). The Application of Digital Twins in the Field of Fashion. In: Lv, Z., Fersman, E. (eds) Digital Twins: Basics and Applications. Springer, Cham.

Khomariah, Sinta, Rina Febriana, and Vera Utami Gede Putri. (2025) "The Influence of Clo3D Software on Sustainable Fashion Practices: A Comprehensive Literature Analysis." Global Synthesis in Education Journal 3.1: 48-56.

Healthcare

Business Function: Scheduling Appointments

- Task: Effectively set medical appointments
- Productivity measure: $\frac{\text{Success Rate in Making an Appointment *(1-Prob no-show)}}{\text{Patient Time+Admin Time}}$.

Calculations:

- Success rate: Success rate in scheduling over the phone is 72%, while online it is 93%. Hasvold and Wootton (2011), North et al. (2021). Success in scheduling face-to-face is assumed to be 100%.
- No-show rate: No-show rates after reminder phone calls by staff were 13%; after automatic reminders were 17%, and after no reminder 23%, Parikh et al. (2010). We assume that a reminder call can be made after in-person and over-the-phone appointments. We assume that this takes 3 minutes for the staff and 1.5 minutes for the patient. No reminder is made after online appointments without an automatic reminder. Automatic reminder is made for online appointments with automatic reminders. Automatic reminder takes 1 minute for the patient.

Assumptions:

- In person: it takes 15 minutes of patient time to schedule a face-to-face, while it takes 5 minutes of admin time
- Over the Phone: It takes 8 minutes of patient time and 5 minutes of admin time to schedule over the phone (Accenture, 2018)
- Online without an automatic reminder: It takes 3 minutes of patient time to conduct an appointment online, regardless of whether it includes an automatic reminder. (The

UCSF case study describes that online appointments include 4-7 questions. To this, we have to add the time to log into the system, which raises the time to 3 minutes.) Online with automatic reminder:

References:

Accenture, Insight driven health: why first impressions matter, 2018.

Hasvold P. and Richard Wootton "Use of telephone and SMS reminders to improve attendance at hospital appointments: a systematic review" Journal of Telemedicine and Telecare 2011; 17: 358–36.

North F, Nelson EM, Majerus RJ, Buss RJ, Thompson MC, Crum BA "Impact of Web-Based Self-Scheduling on Finalization of Well-Child Appointments in a Primary Care Setting: Retrospective Comparison Study" JMIR Med Inform 2021;9(3), 23450.

Parikh et al. (2010) "The Effectiveness of Outpatient Appointment Reminder Systems in Reducing No-Shows Rates" The American Journal of Medicine 123, 542:548.

UCSF case study "Self-scheduling for specialty care" May 31, 2023 (https://cdhi.ucsf.edu/case-study-self-scheduling-specialty-care)

Tracking medication administration

- Task: Monitor the administration of medication to patients.
- Productivity measure: % of events without a serious ADE.

Calculations:

- Probability of ADE: 6.5 per one hundred non-obstetrical admissions (Bates et al, 1995).
- Reduction in ADE rate after using barcodes 0.2/.26.
- Probability of administration of medicine without ADE is 1-.065=.935 with pencil and paper and 1-0.65*0.2/0.26=0.95 with barcode.

References:

Truitt, E. R. Thompson, D. Blazey-Martin, D. NiSai, D, Salem. (2016) "Effect of the Implementation of Barcode Technology and an Electronic Medication Administration Record on Adverse Drug Events" Hospital Pharmacy,51(6):474–483.

Bates DW, Cullen DJ, Laird N et al. (1995) Incidence of adverse drug events and potential adverse drug events: Implications for prevention. JAMA. 274:29–34.

A.4 Sampling Frame

The sampling frames were based on the most comprehensive and latest establishment census available from national statistical agencies or administrative business register. Table A.21 provides the main data sources used in the sample frame for each country.

Table A.21: Sampling frame by country

Country	Source	Sampling frame	Year
Bangladesh	Bangladesh Bureau of Statistics.	Est. census, 2013	2019
Brazil	Ministry of Labor	Employer census, RAIS, 2018	2019
Burkina Faso	Business Registry	Business Registry	2021
Cambodia	Tax Registry	Tax Registry	2022
Chile	Business Registry	Census on Establishments	2022
Croatia	Financial Agency (FINA)	FINA Data	2023
Ethiopia	Ministry of Trade and Industry (MoTI)	Business Registry	2022
Georgia	National Statistics Office of Georgia	Est. census, 2021	2022
Ghana	Ghana Statistical Service	Est. census, 2013–18	2021
India	Central Statistics Office of India	Est. census, 2013–17	2020/23*
Kenya	Kenya National Bureau of Statistics	Est. census, 2017	2020
Korea, Rep.	Statistics Korea	Est. census, 2018	2021
Poland	Statistics Poland	Est. census, 2020	2021
Senegal	National Agency for Statistics (ANSD)	Est. census, 2016	2019
Vietnam	General Statistics Office of Vietnam	Est. census, 2018	2019

Note : * The states of Tamil Nadu and Uttar Pradesh were surveyed in Wave 1 in 2020. The states of Gujarat and Maharashtra were surveyed in 2023.

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

Table A.22: Total number of firms in the universe covered by the survey

Country	Total	Sector			Size		
		Agri.	Manu.	Serv.	Small	Medium	Large
Bangladesh	15,358		15,358		4,164	3,425	7,769
Brazil*	23,364	392	4,758	18,214	12,771	8,955	1,638
Burkina Faso	57,328	4,808	7,493	45,027	40,189	13,284	3,855
Cambodia	8,172		1,890	6,282	5,842	1,287	1,043
Chile	104,854	7,419	11,943	85,492	65,425	30,071	9,358
Croatia	22,350	524	5,387	16,439	17,038	4,381	931
Ethiopia	144,583	3,670	6,553	134,360	105,038	36,798	2,745
Georgia	14,839	313	2,194	12,332	10,815	3,259	765
Ghana	42,165	880	10,284	31,001	30,133	10,070	1,962
India**	616,833	71,464	233,684	311,685	624,452	70,928	13,514
Kenya	74,255	3,680	5,407	65,168	50,584	16,676	6,995
Korea, Rep.	545,515	1520	167,466	376,529	450,264	82,403	12,848
Poland	244,983	3,021	52,340	189,622	198,107	37,799	9,077
Senegal	9,583	1,051	4,069	4,463	7,805	1,414	364
Vietnam	179,713	1,080	45,805	132,828	135,046	33,107	11,560
Total	**2,103,895**	**117,070**	**567,829**	**1,432,427**	**1,756,723**	**350,188**	**75,612**

Note : * Brazil refers to state of Ceará; ** States of Tamil Nadu, Uttar Pradesh, Gujarat, and Maharashtra in India. The survey does not cover agriculture or services in Bangladesh, nor agriculture in Cambodia. In India, only the states of Gujarat and Maharashtra have agriculture included in the survey. Table 2 provides the distribution of the number of firms sampled in each country, by sector and firm size group.

We exclude micro-firms with fewer than 5 employees. Micro firms, particularly in developing countries, are more likely to be informal (Ulyssea, 2018), making them less likely to be captured in the sampling frame; and this would require further adjustment in the survey instrument and sampling design.[43] This size threshold is aligned with other firm-level standardized surveys with comparability across countries. The World Bank Enterprise Survey (WBES) also uses a threshold of 5 employees. The World Management Survey (WMS) uses a threshold of 50 employees.

We stratify the universe of establishments by firm size, sector of activity, and geographic regions. Our sample is representative across these dimensions. In the firm size stratification, we have three strata: small firms (5-19 employees), medium firms (20-99 employees), and large firms (100 or more employees). Regarding sector, for all countries, we stratified at least for agriculture (ISIC 01), food processing (ISIC 10), Wearing apparel (ISIC 14), Retail and Wholesale (ISIC 45, 46 and 47), other manufacturing (Group C, excluding food

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

processing and apparel), and other Services (including all other firms, excluding retail). We use this sector structure of the data for most of the analysis in this paper. Additional sector stratification that were country specific included: motor vehicles (ISIC 29); Leather (ISIC 15), Pharmaceutical (ISIC 21), and Motor vehicles (ISIC 29); and Land transport (ISIC 49), Finance (ISIC 64), and Health (ISIC 86).[44] In the geographic stratification, we use sub-national regions.

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

The data used in this paper corresponds to the first and second phase of the survey implementation. The surveys were administered between June 2019 and the end of 2021 by the World Bank in partnership with public or private local agencies across ten countries: Bangladesh, Brazil (the state of Ceará), Senegal, and Vietnam in the first phase until January 2020. In the second phase, conducted during the COVID-19 pandemic, after January 2020, included Burkina Faso, India (the states of Tamil Nadu and Uttar Pradesh), Ghana, Kenya, Poland, and the Republic of Korea. The mode of data collection was face-to-face before the pandemic and mostly on the telephone during the pandemic.

Table A.23: Year and mode of data collection

Country	Year	Mode
Bangladesh	2019	Face-to-face
Brazil	2019	Face-to-face
Burkina Faso	2021	Telephone
Cambodia	2022	Telephone
Chile	2022	Telephone
Croatia	2023	Online
Ethiopia	2022	Face-to-face
Georgia	2022	Online & Telephone
Ghana	2021	Telephone
India	2020/23*	Face-to-face
Kenya	2020	Telephone
Korea, Rep.	2021	Telephone
Poland	2021	Telephone
Senegal	2019	Face-to-face
Vietnam	2019	Face-to-face

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

A.5 Survey Weights

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

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

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

where n_{isr} is the number of establishments targeted by the survey for stratum isr, and N_{isr} is the number of establishments in the sampling frame for the same stratum. Accordingly, the design weights of establishments are:

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

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

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

$$w_{isrk} = \frac{d_{isrk}}{\hat{\theta}_{isr}} = \frac{d_{isrk}}{m_{isr}/n_{isr}} = \frac{N_{isr}/n_{isr}}{m_{isr}/n_{isr}} = \frac{N_{isr}}{m_{isr}} \tag{A.3}$$

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

$$\sum_{k \in R_{isr}} w_{isrk} = N_{isr} \tag{A.4}$$

where R_{isr} denotes the respondent sample for stratum isr.

Because of the different number of establishments in each country, when computing global

statistics, we re-scale weights so that all countries are equally weighted.

A.6 Measures to Minimize Bias and Measurement Error During Survey Design and Implementation

During the design of the survey questionnaire a number of good practices were considered in order to minimize different types of potential biases. The literature on survey design has identified three types of potential bias and measurement errors. These depend on whether they originate from the non-response, the enumerator or the respondent (Collins, 2003). In this section we describe all the steps taken in the design and implementation of the FAT survey to minimize these errors.

Non-response bias. A critical potential bias is associated with non-response in particular questions or non-participation in the survey (Gary, 2007). When this non-response follows a pattern that can be linked to factors correlated to the measured object, this non-response is associated with biases. For example, if more technology sophisticated firms refuse to participate because of fear to reveal commercial information, this would result in significant downward bias in estimating the level of technology sophistication. To minimize this risk, we try to maximize participation in the survey and follow three steps. First, we partner with national statistical offices and industry associations to use the most comprehensive and updated sampling frame available, as well as their experience on data collection, which are supported by endorsement letters from local institutions.[45] Having up to date contact details significantly improves response and minimized contact fatigue. Second, we follow a standard protocol in which each firm is contacted several times to schedule an interview. We split the sample in different batches, following the order of randomization within stratum, and provide contact information of subsequent batches only after interviewers have shown evidence that they have exhausted the number of attempts to complete the initial list. Third, we monitor the implementation, validation of skip conditions and outliers (e.g. financial statements' information) in real time using standard survey software, and request that any missing information are completed through a follow up call, checked by supervisors. This minimizes risks that enumerators skip the order of their randomly assigned list of firms.

Enumerator bias and error counts. Minimizing cognitive biases in respondents in face to face and phone interviews starts with making sure that enumerators are able to implement the survey in a clear and consistent manner. To this end, the survey, training, and data collection processes are largely designed to minimize enumerator biases and data collection

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

errors. First, to reduce the likelihood of coding errors, we use closed-ended questions, which make coding the answers a mechanical task, eliminating the reliance on the enumerator's interpretation of the answer and subjective judgement to code them, as it is the case with open-ended questions (Bloom et al., 2016). Second, to make sure that implementation is consistent across enumerators within and between country surveys, we implement the same standardized training in each country with enumerators, supervisors, and managers leading the data implementation. The training is led by team members directly involved in the elaboration of the questionnaire and implemented in local languages - English, French, Portuguese and Vietnamese,[46] and they include vignettes to ensure that enumerators understand the specific technologies they are asking about. The two to three days training consists of one general presentation about the project, covering the main motivation, relevance, coverage, and protocols that should be used to approach the interviewees and the review of the full questionnaire (question by question). The training material includes pictures of each technology mentioned in the survey both in general and sector-specific business functions, which are shared with enumerators. After going over the full questionnaire and clarifying any questions that emerge, the participants of the training conduct a mock interview using CAPI, under the supervision of our team.

Third, to guarantee that translations use words that are understood by firms managers, in each country we conduct a pre-test pilot of the questionnaire with firms out of the sample. A pilot of the questionnaire is implemented in each country with firms out of the sample. This allows to fine-tune questions to the local language, finalize the translation and select the most relevant examples in each question. After the pilot, our teams have the opportunity to discuss with the managers implementing the questionnaires and clarify any potential question over the implementation process.

Fourth, to attain greater quality control during the data collection process, enumerators record the answers via *Computer-Assisted Personal Interviews* (CAPI) and *Computer-Assisted telephone Interviews* (CATI) software.[47] Using CAPI/CATI has clear advantages. First, it allows the use of logical conditions and skips which prevent data inputting errors and omitting questions, and also reduces the potential for abnormal values or non-response to specific questions. Second, it reduces substantially the time of implementation of the survey, increasing the quality of responses and minimizing survey fatigue. Supervisors are assigned to review all interviews, identifying missing values and abnormal responses. In addition, the CAPI/CATI system can identify when enumerators complete the survey too fast and

[46] In the case of Vietnamese, we used translation services support.

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

other abnormal issues that can raise concerns about the quality of the interview. Finally, CAPI/CATI also allows for the core team to regularly monitor the data collection process and use standard algorithms to analyze the consistency of the data at different stages of data collection and by watches, thus providing continuous feedback and quality control.

Respondent bias. Perhaps the most important type of bias relates to cognitive biases from respondents. These biases can be large in surveys with open ended questions or where concepts can be largely subjective. Specifically, two broad groups of factors can trigger response errors: *cognitive*, which affect the comprehension of the questions, and *framing*, which may cause biased answers due to the perceived socially (un)desirability of the answers (Bertrand and Mullainathan, 2001). We take several steps to minimize this respondent bias. First, surveys need to be responded by the appropriate person in the firm that has all the information needed to respond. During the implementation of the screening process we ensure that the interview is arranged with the appropriate person or persons (Bloom et al., 2016). Senior managers (and in larger firms other managers such as plant managers) are asked to respond to the sections that cover the technologies used, and HR managers are asked to respond the questions on employment. Second, when possible use face-to-face interviews, which lead to higher response rates and lower respondent bias and measurement errors than web-based interviews.Only during the pandemic and due to existing mobility restrictions, we implemented surveys on the phone. Third, as discussed above, the use of a closed-ended design in the questionnaire reduces measurement error in the answers as the respondent is questioned about specific technologies (one at a time), and only when the presence of each of the possible technologies is established, the question about the most widely used technology is triggered. While this increases the length of the interview, it also increases the reliability of the data collected. Fourth, also as discussed above, we pre-pilot the questionnaire in each country to ensure that questions are clear in their wording in the specific geographical and cultural contexts, simple, and objective, so that the response does not require any subjective judgement (Bertrand and Mullainathan, 2001). Fifth, and more importantly, to avoid *social desirability bias*, by which respondents may overstate the use of more sophisticated technologies, the survey avoids the words “technology" and “sophistication" and employs more neutral terms such as “methods" and “processes". In addition, the survey is administered so that the respondent does not know all the possible technologies in a business functions before asserting whether a technology is used in the firm.[48] This reduces the risk that managers are framed to bias responses to the more advanced (socially desirable) technology, since they don’t know what they will be asked in advance. Finally, when possible, enumerators are instructed to visually verify the information provided during the interviews. For example,

[48]It also allows for “don’t know" options.

in the case of use of a sophisticated production technology that can be visually identified in the shop floor.

A.7 Ex-post Checks and Validation Exercises

In addition to using best practices in survey design and implementation, it is important to perform validation checks once the data is collected. This allows us to measure the effectiveness of all these efforts to minimize bias and measurement error. In what follows, we describe some of the validation tests performed.

Minimizing potential non-response bias Our survey implementation was designed to minimize non-response through the use of well-prepared agencies and institutions to administer the survey and the presentation of adequate supporting letters to encourage participation. Table A.24 shows response rates by country, firm size group and sector. Response rates vary between 15% in Croatia and 86% in Georgia.

Table A.24: Response rates (by country)

Country	Response rate
Bangladesh	30%
Brazil	39%
Burkina Faso	45%
Cambodia	16%
Chile	40%
Croatia	15%
Ethiopia	42%
Georgia	86%
Ghana	49%
India	49%
Kenya	77%
Korea*	24%
Poland	47%
Senegal	57%
Vietnam	80%
Average across countries	**46%**

These are unweighted response rates calculated as the ratio between firms that responded the survey and the total number of firms in the sample which we attempted to conduct the interview. The high response rate for Vietnam is associated with the fact that the survey was implemented by the national statistical office. In most cases, these response rates are high relative to typical response rates in firm-level surveys, which for the U.S. are around 5 to 10 percent, and are consistent with response rates observed for WMS and MOPS (Bloom

et al., 2016).[49]

To minimize potential non-response bias, we adjusted the sampling weights for unit non-response. The non-response adjustment was calculated at the strata level, so that the weighted distribution of our respondent sample across strata (sector, size, region) exactly matches the distribution of establishments in the sampling frame.

More importantly, to check the reliability of the instrument we implemented a series of ex-post tests in the first phase of the survey, focusing on countries we implemented the survey first. First, we study whether, in the sample of contacted firms, there are significant differences between those that responded and those that declined participating or could not be reached. The only information available in all firms we attempted to contact in the three sampling frames is the number of employees. Table A.25 tests whether there are differences in employment between the respondent and non-respondent groups, controlling for characteristics used for stratification. We find no significant differences in firm size between respondents and non-respondents in any of the three countries.

Table A.25: Comparison of establishment size between respondents vs non-respondents

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

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

Second, under the premise that any systematic relationship between firm characteristics and participation is continuous in their reluctance to participate in the survey, we can learn about sample differences between respondents and non-respondents by comparing firms across different percentiles of the distribution of the number of attempts it took for them

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

to respond the survey.[50] For Senegal, we explore whether after controlling for observable characteristics, there are significant differences in average technology sophistication in GBFs between firms that required a larger number of attempts to be contacted (top quartile) and those that did not. Table A.26 shows that there are no statistically significant differences in technology sophistication between the two groups.

Table A.26: Comparison of technology sophistication between high and low number of attempts

VARIABLES	Senegal	Senegal
Top quartile of attempts (4 or more)	-0.021	-0.027
	(0.020)	(0.019)
Observations	1,753	1,666
R^2	0.377	0.437
Controls:		
Sector FE	Y	Y
Size-group FE	Y	Y
Region FE	Y	Y
Age		Y
Exporter		Y
Foreign owned		Y

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

Third, we compare firms that were in the first sample list provided to enumerators and those in subsequent lists. Table A.27 show that there are no statistically significant differences between the two groups.

In each of these exercises, we find no statistical difference in the number of employees, technology sophistication, wages, and share of workers by skill and education between firms in the group that proxies for the response sample and the group of firms that proxies for the non-response sample.[51]

Minimizing enumerator bias. To minimize the potential for enumerators to introduce biases when administering the survey, we conduct in each country the same standardized training and piloting prior to going to the field. We also conduct ex-post tests to identify

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

[51] See Table A.25 to A.31 in Appendix A.

Table A.27: Comparison of technology sophistication between original and replacement sample

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

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

abnormal interviews or outliers by running regressions of firm-level sophistication on enumerator dummies and firm controls as discussed in the text. Table A.28 shows that enumerator dummies are not significant for Brazil, Ghana, India, and Korea. For Bangladesh, Senegal, Vietnam, and Kenya, no more than 20% of enumerator dummies are statistically significant with respect to their distribution towards the type of firms they interview across various strata. Table A.29 compares the average technology sophistication ($MOST_j$) for GBF, excluding the firms with abnormal enumerators and in the entire sample. We find no economic or statistical difference between mean sophistication in these countries.

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

To assess the relevance of response bias, we conduct a parallel pilot in Kenya where

Table A.28: Analysis of enumerator bias distribution

VARIABLES	Brazil	Vietnam	Senegal	Bangladesh
Share of Significantly Different Interviewers	0	0.09	0.08	0.11
Number of Significantly Different Interviewers	0	13	2	4
Number of Interviewers	8	145	25	37
	Ghana	India	Korea	Kenya
Share of Significantly Different Interviewers	0	0	0	0.2
Number of Significantly Different Interviewers	0	0	0	2
Number of Interviewers	44	18	9	10

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

we re-interview 100 randomly selected firms with a short version of the questionnaire. For those firms, we randomly select three business functions and ask about the presence of the relevant technologies.[52] Both the original and back-end interviews in the pilot are conducted by phone by different interviewers.

Despite using phone interviews which are subject to greater measurement error than face-to-face interviews, comparison of answers from the pilot reveals that 73% of the answers were the same across the two interviews.[53] We estimate a probit model to assess the likelihood of consistent answers between the original and the back-check interviews, controlling for firm-level fixed-effect. Reporting the use of a technology in the back-check interview is associated with 80.6% of likelihood of reporting the use of the same technology in the original interview. Conversely, reporting that a technology is not used in the back-check interview, is associated with a 29.3% likelihood of being reported in the original survey.

Additional validation exercise with employer-employee census (RAIS) in Brazil

Some final ex-post checks were conducted with the Brazil data and takes advantage of the fact that we have access to the RAIS administrative data, which is a matched employer-employee dataset that covers the universe of firms in the sampling frame. This allows us to

[52]The pilot coincided with the beginning of the data collection for phase two which includes new countries, and Kenya is one of them. Despite the fact that Kenya is not in the sample, the pilot is informative about the significance of response bias. The re-interviews produce 1,661 answers (106 interviews times 3 business functions times an average of 5.2 technologies per function).

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

Table A.29: Difference in technology sophistication in general business functions with and without outlying enumerators

	All Sample	Sample Without Different Enumerators	Difference
Vietnam			
Mean	1.934	1.947	-0.013
SE	(0.012)	(0.012)	(0.017)
Observations	1,499	1,341	
Senegal			
Mean	1.406	1.404	0.002
SE	(0.011)	(0.011)	(0.016)
Observations	1,786	1,784	
Bangladesh			
Mean	1.482	1.458	0.024
SE	(0.015)	(0.015)	(0.021)
Observations	903	798	
Kenya			
Mean	1.938	1.936	.002
SE	(0.020)	(0.020)	(0.029)
Observations	1305	1296	

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

compare variables in RAIS with variables we collected in FAT for the same firms.

First, we analyze the correlation between sales per worker and our technology measures (GBF) and (SBF) from FAT and average wages from RAIS. Table A.30 reports the point estimates of regressing firm-level FAT variables on the log or average wages per worker from RAIS and a set of firm-level controls. The FAT variables are log of sales per worker (column 1), and average technology sophistication (GBF, column 2, and SSBF, column 3). In all three cases we find strong positive associations between the FAT and the RAIS variables.

Second, we compare the differences between labor-related indicators from a matched employer-employee administrative data for firms in FAT versus the universe of firms. To perform this comparisons we obtained the weighted average for firms in FAT, using the weights we constructed as described in section A3 and compare it with the average for all

Table A.30: Relationship between FAT survey variables and log of wages from administrative data for Brazil

Variable	(1) log(sales per worker)	(2) GBF	(3) SSBF
ln(Wage) RAIS	0.882***	0.400***	0.299***
	(0.157)	(0.111)	(0.101)
Observations	592	675	674
R-squared	0.346	0.364	0.800
Controls:			
Sector FE	Y	Y	Y
Region FE	Y	Y	Y
Size-group FE	Y	Y	Y
Age	Y	Y	Y
Exporter	Y	Y	Y
Foreign owned	Y	Y	Y

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

firms in RAIS that are part of our universe for the State of Ceará, in Brazil [54]. We then perform a t-test to compare the differences. Table A.31 shows that the differences are not statistically significant.

Overall, these ex post checks appear to validate the quality of the data collected.

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

Table A.31: Comparison between FAT sample and RAIS data (universe)

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

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

B Construction of Measures

This section provides details about the construction of the various technology.

B.1 Technology Measures

The technology measures at the business function (BF) level that are discussed in the text are as follows - N_f, $ANUM_{f,j}$, $NUM_{f,j}$, $MAX_{f,j}$, and $MOST_{f,j}$. The means of all of these BF-level measures are reported in **??**. To better understand the construction of these variables, it is helpful to understand the structure of the corresponding questions asked. The figure below provides an example question asked for a particular business-function (BF) in the "Livestock" Sector. The presence of each of the technologies is calculated as a binary variable taking values 0 and 1.[55]

Question: Does this establishment use any of the following methods for breeding or genetic procedures?	Answer	
Breed substitution	1 = Yes 0 = No	. = Don't know
Inbreeding or Crossbreeding	1 = Yes 0 = No	. = Don't know
Artificial insemination (AI)	1 = Yes 0 = No	. = Don't know
Selective breeding based on molecular genetics (marker-assisted selection, PCR, DNA sequencing, transgenesis, cloning, genomics)	1 = Yes 0 = No	. = Don't know
Other	1 = Yes 0 = No	. = Don't know

Question: What is the breeding or genetic method used more often in this farm?	Answer 1 = Breed substitution 2 = Inbreeding or Crossbreeding 3 = Artificial insemination (AI) 4 = Selective breeding based on molecular genetics (marker-assisted selection, PCR, DNA sequencing, transgenesis, cloning, genomics) . = Other . = Don't know

Figure B.1: Example question for the presence of technologies and most-used technology

If a respondent answers that they use more than one technology in the BF, then they are asked about the most-used technology in that BF.[56]

[55] If a respondent answers "Don't know", that is coded as missing. We also do not take into account technologies outside the grid (Other).

[56] Again here, if the answer is "Don't know", or "Other", we assign it a missing value.

After constructing these technology-level binary variables and the variable for most widely-used technology (which are at establishment-BF level), we move on to constructing the N_f, $ANUM_{f,j}$, $NUM_{f,j}$, $MAX_{f,j}$, and $MOST_{f,j}$, variables. The details and formulae used to construct each of these variables are listed below -

N_f : This simply denotes the number of technologies in the grid that exist for business function f. This does not depend on the answers provided by the survey respondents, and takes the same value for a particular BF, across all establishments[57].

$ANUM_{f,j}$: $ANUM_{f,j}$ denotes the absolute number of technologies used by an establishment in a specific business function. This variable is calculated by counting the number of technologies in a BF that the establishment confirmed using. Note that $ANUM_{f,j}$ will *always* be less or equal than N_f.

$NUM_{f,j}$: This denotes the relative number of technologies and is calculated using the following formula: $NUM_{f,j} = \frac{ANUM_{f,j}-1}{N_f-1} * 4 + 1$. This variable is an afine transformation of $ANUM_{f,j}$. We subtract 1 from both the numerator and denominator of the ratio in the formula so that this ratio ranges from 0 to 1. By multiplying this ratio by 4 and adding 1, the resulting measure ranges from 1 to 5 in all business functions of all establishments, hence allowing for comparability.

$MAX_{f,j}$: $MAX_{f,j}$ denotes the sophistication level of the most-sophisticated technology used by the establishment in the BF. It is calculated using the formula: $MAX_{f,j} = \frac{r^{MAX}_{f,j}-1}{R_f-1} * 4 + 1$, where $r^{MAX}_{f,j}$ is the absolute rank of the most sophisticated technology used in a BF, and R_f is the rank of the most sophisticated technology **possible** in the BF f. For most BFs, R_f equals N_f.[58] However, there are a few exceptions where the number of technologies in the grid for ta BF does not equal the rank of possibly most sophistication technology. These exceptions are discussed in Appendix B.1.1. We apply the same afine transformation to the relative ranks so that the range of $MAX_{f,j}$ is $[1, 5]$.

$MOST_{f,j}$: $MOST_{f,j}$ denotes the sophistication level of the most widely-used technology in a particular BF by the establishment. It is calculated using the formula: $MOST_{f,j} =$

[57]For instance in the example in Figure B.1, the value that N_f takes here is 4 for all establishments. Again, this does not include the "Other" technology, as it is not specified in the grid.

[58]For example, if a respondent answered "Yes" to "Breed substitution", "Inbreeding", and "Artificial Insemination", and "No" for all other technologies, $r^{MAX}_{f,j}$ would be 3 for that establishment for this BF. Here $R_f = N_f = 4$, so $MAX_{f,j}$ would be 3.67.

$\frac{r_{f,j}^{MOST}-1}{R_f-1} * 4 + 1$, where $r_{f,j}^{MOST}$ is the absolute rank of the most widely-used technology in a BF, and R_f is the rank of the most sophisticated technology possible in BF f.[59] The relative sophistication ranking is subject to an afine transformation so that the range of $MOST_{f,j}$ is $[1, 5]$.

After constructing the measures at the establishment-BF level, we construct establishment-level measures by averaging them across all the BFs of each establishment. In particular, NUM_j, MAX_j, and $MOST_j$ are calculated as follows -

$$S_j = \sum_{f=1}^{N_j} \frac{S_{f,j}}{N_j} \tag{B.5}$$

where $S \in \{NUM, MAX, MOST\}$, and N_j is the number of BFs conducted in establishment j.

B.1.1 Exceptions

As mentioned above, there are some exceptions to the calculation of $MAX_{f,j}$ and $MOST_{f,j}$ statistics for particular business functions. These exceptions are limited to two sectors - Automotives (Motor Vehicles) and Health.

Automotives - As specified in Figure A.5, in BFs "Body Pressing", "Painting", and "Plastic Injection Molding", although the number of technologies is more than 2, there are sub-BFs, where the ranking of technologies is only 2 (basic and advanced). For instance, in "Body Pressing", there are three distinct sub-BFs - "pressing of skin panels", "structural components", and "welding of main body" (refer to Figure A.5). As such, if the ranking of the technologies were to take the value of the technology as per the questionnaire, that would be erroneous. Another example is provided in Figure B.2 for the question related to Body Pressing. Consider for example, an establishment answering "Yes" to 1st, 2nd, 3rd, and 6th technologies, and for intensive margin answering "3".

If we were to calculate scaled-up $MAX_{f,j}$ and $MOST_{f,j}$ values for this establishment in body pressing, as we do for all other BFs, it would be equal to "5" and "2.6" respectively (if we take $R_f = N_f = 6$). However, this is incorrect, as the 1st, 2nd, 3rd, and correspondingly, 4th, 5th, and 6th technologies are related to the parallel sub-BFs respectively. Hence, we assign

[59] For example, if an establishment that uses "Breed subsbtitution", "Inbreeding" and "Artifical insem.", but uses "Inbreeding" most often, $r_{f,j}^{MOST}$ would be 2. Consequently, $MOST_{f,j}$ would be 2.33, for this establishment in this BF.

Question: Does this establishment use any of the following body pressing and welding methods?	Answer	
Pressing of skin panels using operators	1 = Yes 0 = No	. = Don't know
Pressing of structural components using operators	1 = Yes 0 = No	. = Don't know
Welding of main body using operators	1 = Yes 0 = No	. = Don't know
Pressing of skin panels automated using robotics	1 = Yes 0 = No	. = Don't know
Pressing of structural components automated using robotics	1 = Yes 0 = No	. = Don't know
Welding of main body automated using robotics	1 = Yes 0 = No	. = Don't know
Other	1 = Yes 0 = No	. = Don't know

Question: What is the pressing and welding method used more often in this facility?	Answer 1 = Pressing of skin panels using operators 2 = Pressing of structural components using operators 3 = Welding of main body using operators 4 = Pressing of skin panels automated using robotics 5 = Pressing of structural components automated using robotics 6 = Welding of main body automated using robotics . = Other . = Don't know

Figure B.2: Question for Extensive and Intensive Margins of Tech. in Body Pressing

rank "1" to the first three technologies, and rank "2" to the last three technologies, and take an arithmetic mean to calculate r_j^{MAX}. So in the example, the most sophisticated technology for the establishment in "pressing of skin" would be rank 1, and both, in "pressing of structural panels" and "welding", would be 2. Effectively r_j^{MAX} would then be an arithmetic mean of $\{1,\ 2,\ 2\}$ which is "1.6". Accordingly, value of R_f would be 2, and hence the corrected scaled-up value of MAX and MOST for this estab. in this BF, would be "3.4" and "3" respectively.

Table B.2 shows the adjustment made to the ranks in these BFs before calculation of $MAX_{f,j}$ and $MOST_{f,j}$.

Health - The exceptions in this sector come from two BFs - "Health Equipment" and "Procedures". Firstly, in "Health Equipment" the number of technologies is 11 (see **??**), but there exists no clear ranking. For that reason, to calculate $MAX_{f,j}$ and $MOST_{f,j}$ for this

Table B.2: Adjustment of Ranks in Automotive BFs

Business Function	Sub-Business Functions	Technologies	Rank in Data	Adjusted Rank	R_f	N_f
Body Pressing and Welding	Pressing of Skin Panels	using Operators	1	1	2	6
		using Robots	4	2	2	6
	Pressing of Structural Components	using Operators	2	1	2	6
		using Robots	5	2	2	6
	Welding of Body Parts	using Operators	3	1	2	6
		using Robots	6	2	2	6
Painting	Water-Based	using Operators	1	1	2	4
		using Robots	3	2	2	4
	Solvent-based	using Operators	2	1	2	4
		using Robots	4	2	2	4
Plastic Injection Modelling	Molding of non-visible interior plastic	using Operators	1	1	2	4
		using Robots	3	2	2	4
	Molding of plastic exterior body parts	using Operators	2	1	2	4
		using Robots	4	2	2	4

Notes : The table shows the ranking of technologies in these three BFs of Automotives sector.

BF is difficult. As a result, the value of $MAX_{f,j}$ and $MOST_{f,j}$ is taken to be the same as the value of $NUM_{f,j}$ (which is the relative number of technologies used by an establishment in the BF), for this particular BF.

Coming to "Procedures", both in the data and questionnaire, the questions regarding different procedures are asked individually (see Figure A.10). There are 4 types of procedures - Sepsis Treatment, Childbirth, Trauma, and treatment of Myocardial Infarctions/Strokes. For each of these procedures, there are two corresponding technologies. When the question is asked to the respondent, there are 5 possible options that they could reply, namely - "It is always available", "It is NOT always available", "It is NEVER available", "Don't know", and "Not applicable". For the purpose of classification, firstly the responses for each technology are collapsed into binary variables, taking values 1 for the "always available" option, and 0 for "NOT always" and "NEVER available" options. Just like in other BFs, value of "Don't Know" and "Not Applicable" is considered as missing. After the re-coding, these 4 questions are collapsed into one "Procedures" question that would have 8 technologies. Similar to "Health Equipment", there is no clear ranking to technologies there, hence the value of $MAX_{f,j}$ and $MOST_{f,j}$ is taken to be the same as the value of $NUM_{f,j}$ for this particular BF.

C Additional Figures and Tables

C.1 Figures

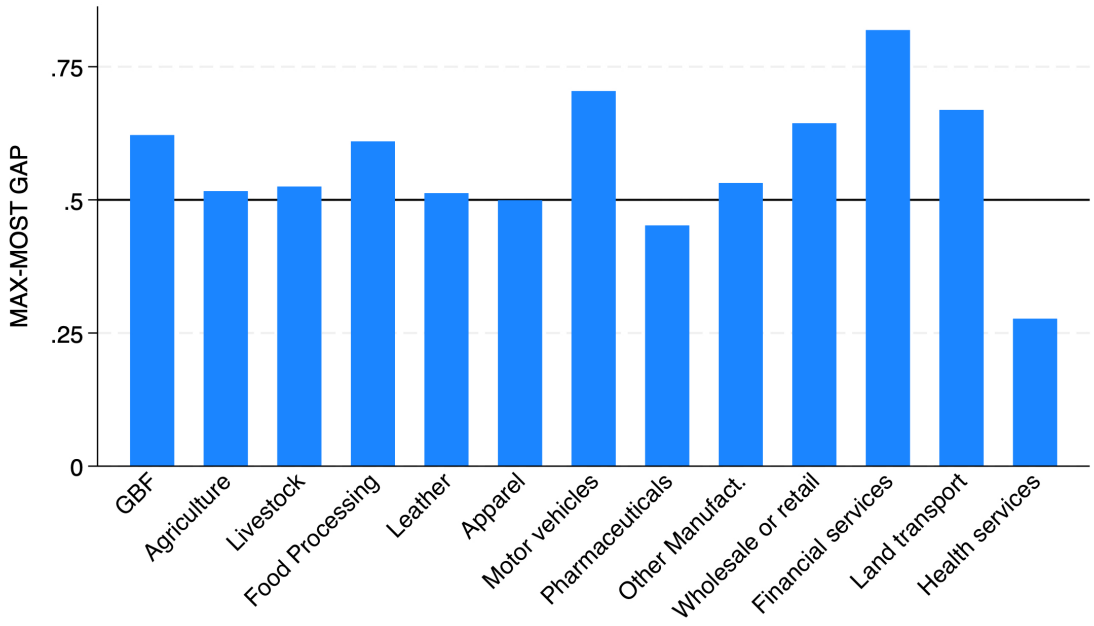
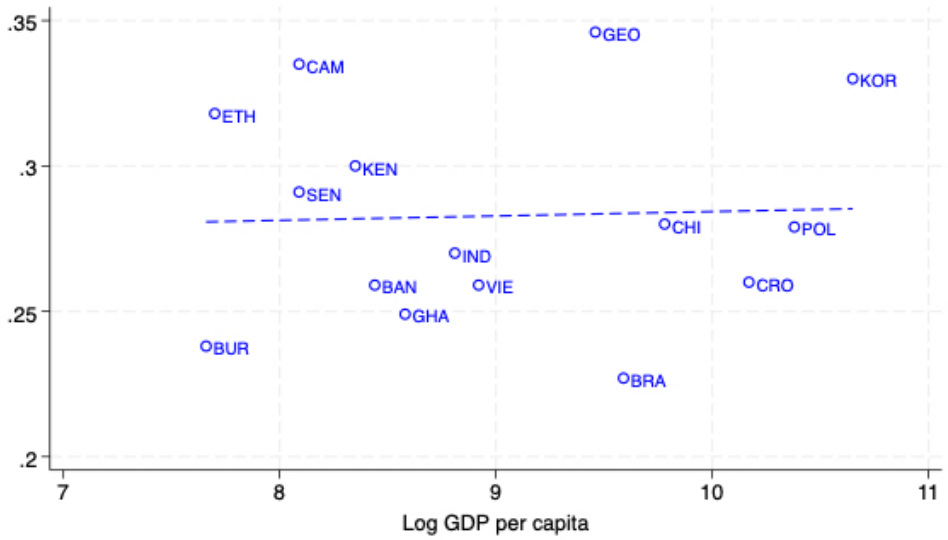


Figure C.3: Average MAX and MOST GAP by Class of Business Function

Note: Figures displays the average across relevant establishments of the share of business functions f in a given class of functions (e.g., GBF or SSBF in the sector) where $MAX_{f,j} > MOST_{f,j}$ and $NUM_{f,j} > 1$.

Figure C.4: Within-country dispersion in MAX-MOST Gaps



Note: The within-country dispersion of the MAX-MOST gaps is the standard deviation of the MAX-MOST gaps of all establishments in the country. Establishments are weighted by sampling weights.

C.2 Tables

Table C.1: Summary Statistics

	All			Small (5-10)		Medium (11-99)		Large (100+)	
	N	Mean	p50	N	Mean	N	Mean	N	Mean
Total # of employees	18570	33.95	9.00	9909	8.45	5477	38.03	3184	492.04
% of workers with college	17686	30.15	20.00	9520	30.79	5144	27.71	3021	28.12
Management practice (z-score)	20739	0.00	0.27	11029	–0.09	6098	0.25	3610	0.53
Sales per worker	15355	11.45	11.43	8121	11.47	4545	11.39	2689	11.25
		Share			Share		Share		Share
Multi-establishment		18.4%			12.1%		20.5%		33.9%
Multinational		17.6%			16.4%		16.4%		23.7%
Exporter		16.8%			8.1%		18.1%		41.0%
Age:									
1–5 Years		17.9%			22.2%		15.2%		9.3%
6–10 Years		21.3%			24.1%		19.6%		15.4%
11–15 Years		17.9%			18.4%		17.2%		17.4%
16+ Years		42.9%			35.3%		47.9%		57.9%
Has electricity, computer and internet		77.1%			67.0%		85.7%		95.0%
Sector:									
Agriculture		5.1%			5.1%		5.2%		5.1%
Livestock		1.9%			2.2%		1.7%		1.4%
Food Processing		10.2%			8.9%		11.8%		11.3%
Apparel		7.4%			6.9%		6.4%		10.5%
Motor vehicles		2.9%			2.0%		3.2%		5.0%
Pharmaceuticals		2.7%			1.5%		3.2%		5.3%
Wholesale or retail		14.7%			18.0%		12.4%		8.6%
Financial services		3.4%			3.2%		4.0%		2.6%
Land Transport		5.0%			5.0%		5.2%		4.3%
Health Services		4.4%			2.1%		5.5%		9.5%
Leather		2.2%			2.2%		1.8%		2.7%
Other Manufacturing		15.8%			16.1%		15.1%		16.1%
Other Services		24.4%			26.7%		24.3%		17.6%

Notes: The table reports summary statistics of establishment-level measures and distribution of establishments, in the overall sample, and by size-groups. The top panel consists of summary statistics calculated using establishment-level sampling weights. The bottom panel reports the unweighted shares of establishments belonging to the various groups.

Table C.2: Average level of technology measures

Business Function	*NUM*	*MAX*	*MOST*	*GAP*	*N*	Business Function	*NUM*	*MAX*	*MOST*	*GAP*	*N*
General Business Functions						*Automotive*					
Business Administration	2.1	3.0	2.5	0.5	5	Vehicle Assembly	2.2	2.9	1.2	0.9	6
Production Planning	1.9	2.7	2.2	0.5	5	Body pressing and welding *	2.0	1.2	1.3	0.1	6
Sourcing	1.9	2.3	1.7	0.7	5	Painting *	1.8	1.1	1.1	0.0	4
Marketing	2.0	2.3	1.7	0.7	5	Plastic injection molding *	1.9	1.2	1.1	0.1	4
Sales	1.9	2.4	1.6	0.8	6	Productive assets management	2.6	3.2	2.1	0.8	3
Payment	2.2	3.5	2.7	0.7	7	Fabrication	1.9	2.2	1.6	0.8	6
Quality Control	1.8	2.1	1.6	0.6	4						
Agriculture						*Pharmaceuticals*					
Land Preparation	2.2	3.6	3.0	0.4	4	Facilities	1.8	3.0	2.6	0.7	4
Irrigation	1.7	2.7	2.4	0.4	6	Weighing scale	2.2	4.1	3.7	0.4	4
Weeding	1.9	2.4	2.0	0.5	5	Mixing/Compounding	1.8	2.9	2.4	0.6	5
Harvesting	1.9	2.7	2.1	0.7	5	Encapsulation	2.1	3.8	3.1	0.6	4
Storage	1.8	2.7	2.3	0.6	5	Quality control	2.3	3.3	2.7	0.5	3
Packaging	1.8	2.1	1.7	0.5	4	Packaging	2.0	3.3	2.8	0.6	3
						Fabrication	1.8	2.3	1.9	0.5	6
Livestock						*Wholesale and Retail*					
Breeding	2.4	3.0	2.5	0.3	4	Customer service	2.3	2.5	1.5	0.8	5
Feeding	2.3	3.5	2.7	0.5	7	Pricing	1.9	2.3	1.7	0.7	5
Animal healthcare	3.2	4.3	3.0	0.6	5	Merchandising	1.8	2.1	1.6	0.7	4
Herd management	1.7	2.0	1.3	0.7	7	Inventory	1.7	2.4	2.0	0.5	5
Transport of livestock	2.4	3.5	2.8	0.4	4	Advertisement	2.2	3.0	2.3	0.6	6
Food Processing						*Financial Services*					
Input testing	2.0	2.4	1.6	0.7	4	Customer service	4.1	4.7	2.1	0.8	4
Mixing/cooking	2.6	3.2	2.2	0.6	4	Avoid fraud	2.9	3.5	1.7	0.9	6
Anti-bacterial	2.2	2.8	2.1	0.6	4	Loan applications	3.3	3.8	1.7	0.9	4
Packaging	2.1	2.5	1.9	0.7	4	Credit applications	2.7	3.1	1.8	0.9	4
Food storage	2.2	3.1	2.6	0.5	4	Operational support area	3.4	4.3	3.0	0.6	3
Fabrication	1.6	1.9	1.5	0.5	6						
Wearing Apparel						*Transportation*					
Design	2.0	2.6	1.9	0.7	3	Planning	1.8	2.1	1.6	0.6	4
Cutting	2.0	2.4	1.9	0.6	5	Plan execution	1.9	2.2	1.5	0.8	5
Sewing	2.1	2.8	2.4	0.5	5	Monitoring	1.9	2.4	1.6	0.7	5
Finishing	1.7	2.1	1.7	0.5	5	Performance measurement	1.8	2.2	1.7	0.5	5
Fabrication	1.7	1.9	1.6	0.4	6	Maintenance	1.8	2.3	1.7	0.7	4
Leather and Footwear						*Healthcare*					
Design	2.0	2.4	2.0	0.3	3	Infrastructure and Machines *	2.8	2.8	2.8	0.0	11
Cutting	2.2	2.6	2.1	0.5	5	Appointment and Scheduling	2.3	2.6	1.7	0.7	4
Sewing	2.2	2.5	2.1	0.5	5	Patient records management	2.2	3.0	2.4	0.5	4
Finishing	1.6	1.8	1.5	0.5	5	Healthcare management **	1.9	2.7	0.0	1.0	2
Fabrication	1.5	2.1	1.9	0.4	6	Procedures *	3.0	3.0	3.0	0.0	8
						Other Manufacturing					
						Fabrication	1.7	2.1	1.7	0.5	6

Notes: The table reports the average of $NUM_{f,j}$, $MAX_{f,j}$, $MOST_{f,j}$ and $GAP_{f,j}$ across establishments in each business function f. Averages are calculated using sampling weights. N is the number of technologies in the grid for thebusiness function.

Table C.3: Frequency of Sophistication Gaps by Business Function

Business Functions	SG_j	Business Functions	SG_j
General Business Functions		*Automotive*	
Business Administration	34%	Vehicle assembly	91%
Production Planning	27%	Body pressing and welding	0%
Sourcing	15%	Painting	0%
Marketing	15%	Plastic injection molding	0%
Sales	28%	Productive assets management	3%
Payment	48%	Fabrication	21%
Quality Control	5%		
Agriculture - Crops		*Pharmaceutical*	
Land Preparation	37%	Facilities	7%
Irrigation	48%	Weighing	27%
Pest Control	23%	Compounding	24%
Harvesting	58%	Encapsulation	35%
Storage	11%	Quality Control	12%
Packing	9%	Packaging	15%
		Fabrication	11%
Livestock		*Wholesale and Retails*	
Breeding	13%	Customer Service	13%
Nutrition	60%	Pricing	15%
Animal healthcare	58%	Merchandising	7%
Herd management	67%	Inventory	7%
Transport of Livestock	30%	Advertisement	39%
Food Processing		*Finance*	
Input Test	17%	Customer Service	27%
Mixing Blending Cooking	18%	ID Verification	33%
Anti-bacterial	13%	Loan Application	23%
Packaging	5%	Loan Approval	8%
Food Storage	8%	Operational Support Area	0%
Fabrication	8%		
Wearing Apparel		*Transportation*	
Design	8%	Planning	8%
Cutting	6%	Execution	28%
Sewing	10%	Monitoring	39%
Finishing	9%	Performance Measurement	26%
Fabrication	7%	Maintenance	13%
Leather and Footwear		*Healthcare*	
Design	2%	Infrastructure and Machines	81%
Cutting	13%	Scheduling Appointments	5%
Sewing	2%	Management of Patient Records	5%
Finishing	4%	Healthcare Management	0%
Fabrication	3%	Procedures	51%
		Other Manufacturing	
		Fabrication	22%

Notes: The table reports the percentage of establishments that experience sophistication gaps in each business function. See section 4.1 for the definition of sophistication gaps. The percentages are calculated using sampling weights.

Table C.4: Productivity and Technology Sophistication: Linearity

	ln(Sales per worker)				TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{S}_j$	0.72***		0.58***		0.18*	
	(0.10)		(0.10)		(0.09)	
$\overline{S}_j$* D(High Sophistication))	-0.06		-0.04		-0.03	
	(0.05)		(0.04)		(0.04)	
D($\overline{S}_j < 1.5$) * $\overline{S}_j$		0.50***		0.50***		0.30**
		(0.18)		(0.19)		(0.14)
D($1.5 \leq \overline{S}_j \leq 2.5$) * $\overline{S}_j$		0.66***		0.50***		0.28***
		(0.12)		(0.12)		(0.10)
D($2.5 \leq \overline{S}_j \leq 3.5$) * $\overline{S}_j$		0.64***		0.52***		0.21***
		(0.08)		(0.08)		(0.06)
D($\overline{S}_j \geq 3.5$) * $\overline{S}_j$		0.56***		0.46***		0.18***
		(0.06)		(0.07)		(0.05)
K_j			0.24***	0.24***		
			(0.03)	(0.03)		
H_j			0.20*	0.21*		
			(0.11)	(0.11)		
Constant	8.26***	8.42***	5.91***	6.02***	-0.89***	-1.08***
	(0.34)	(0.38)	(0.34)	(0.42)	(0.16)	(0.20)
N	16666	16666	12677	12677	11272	11272
R-squared	0.32	0.32	0.42	0.42	0.08	0.09
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: D(.) are binary variables that take the value 1 if the establishment satisfies the condition in parenthesis and 0 otherwise. High Sophistication represents that the establishment has above-median S_j. TFP is measured by the Solow residual. See details about its calculation in the paper. All regressions are estimated using establishment-level sampling weights *, ** and *** denote 10%, 5% and 1% significance respectively.

Table C.5: Average GAP, MAX, and MOST along firm's age and size groups

Age	GAP			MAX			MOST		
Group	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
<=5	0.63	0.58	0.60	2.33	2.64	2.80	1.80	2.05	2.10
6-10	0.64	0.61	0.625	2.49	2.83	3.06	1.98	2.08	2.25
11-15	0.61	0.56	0.62	2.54	2.80	3.22	2.00	2.15	2.40
>=16	0.65	0.58	0.55	2.60	3.00	3.46	1.95	2.26	2.67

Notes : Averages of GAP_j, MAX_j and $MOST_j$ across establishments in specific size and country groups. Averages computed using establishment-level sampling weights.

Table C.6: Correlates of MAX-MOST Gaps across establishments by size and country income level

	GAP_j				
	(1)	(2)	(3)	(4)	(5)
H_j	-0.060*	-0.112***	-0.057	-0.081***	-0.045
	(0.035)	(0.041)	(0.072)	(0.026)	(0.057)
D(Rejected Loan)	0.034*	0.043**	0.081***	0.042***	0.048
	(0.017)	(0.022)	(0.023)	(0.013)	(0.045)
mgt_z	0.004	-0.006	-0.016	-0.007	0.025
	(0.008)	(0.010)	(0.013)	(0.007)	(0.016)
Family Business	0.029	0.033	0.071**	0.030	0.085*
	(0.027)	(0.026)	(0.032)	(0.023)	(0.044)
Foreign Owned	0.029	0.101***	-0.021	0.051***	0.016
	(0.019)	(0.026)	(0.038)	(0.013)	(0.099)
Exporter	-0.068**	-0.016	-0.029	-0.022	-0.106***
	(0.031)	(0.023)	(0.028)	(0.016)	(0.038)
Bias	0.009	0.021***	0.016*	0.020***	0.007
	(0.007)	(0.007)	(0.010)	(0.007)	(0.008)
Age: 6 - 10 Years	-0.015	0.055*	-0.020	-0.021	0.035
	(0.025)	(0.031)	(0.038)	(0.019)	(0.054)
Age : 11 - 15 Years	-0.065**	0.016	-0.046	-0.061***	-0.048
	(0.028)	(0.033)	(0.037)	(0.020)	(0.059)
Age : 16+ years	-0.029	0.034	-0.052	-0.020	-0.050
	(0.026)	(0.029)	(0.035)	(0.018)	(0.049)
(mean) num_g1	-0.007**	0.012**	0.030***	-0.007**	0.008
	(0.003)	(0.005)	(0.005)	(0.003)	(0.008)
Constant	0.590***	0.487***	0.179**	0.589***	0.606***
	(0.048)	(0.052)	(0.074)	(0.037)	(0.105)
N	8354	4668	2662	13354	2331
R-squared	0.112	0.205	0.311	0.093	0.072
2-Dig. Sector FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Sample	Small	Medium	Large	Low-income	High-income

Notes: Dependent variable is defined at establishment level as number of BFs with $MAX_{fj} > MOST_{fj}$, over number of BFs with $NUM_{f,j} > 1$. The base category is Age $\leq$ 5 Years. Loan rejected is a binary variable taking value 1 if the establishment has any loan rejected in the last year. Small, medium, and large refer to firm size groups. Low- and High-income countries refer to country groups based on their average per capita income, in which low-income includes all "non high-income" countries. All columns control for the number of business functions where $NUM_j > 1$ –$Multiple_j$. Establishments weighted by sampling weights. *, ** and *** denote 10%, 5% and 1% significance respectively.

Table C.7: Establishment Performance and Technology Sophistication

	ln(Sales per worker)								Profit Rate				TFP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
K_j	0.24***	0.27***			0.24***	0.27***										
	(0.03)	(0.03)			(0.03)	(0.03)										
H_j	0.20*	0.67***			0.25**	0.71***										
	(0.11)	(0.12)			(0.11)	(0.12)										
$\overline{S}_j$	0.50***	0.62***	0.60***	0.81***					0.04***	0.04***			0.11***	0.137***		
	(0.05)	(0.05)	(0.04)	(0.05)					(0.01)	(0.01)			(0.03)	(0.033)		
$MOST_j$					0.46***	0.76***	0.41***	0.89***			0.06***	0.06***			0.10**	0.20***
					(0.06)	(0.06)	(0.06)	(0.07)			(0.01)	(0.01)			(0.04)	(0.04)
MAX_j					0.07	-0.06	0.21***	-0.01			-0.01	-0.01			0.02	-0.04
					(0.05)	(0.06)	(0.05)	(0.06)			(0.01)	(0.01)			(0.04)	(0.04)
Constant	6.02***	5.81***	8.45***	8.75***	6.01***	5.85***	8.45***	8.82***	0.05	0.20***	0.04	0.21***	-0.79***	-0.31***	-0.79***	-0.31***
	(0.31)	(0.37)	(0.32)	(0.28)	(0.31)	(0.36)	(0.32)	(0.29)	(0.04)	(0.05)	(0.04)	(0.04)	(0.09)	(0.09)	(0.09)	(0.09)
N	12677	12677	16666	16666	12677	12677	16666	16666	12206	12206	12206	12206	11272	11272	11272	11272
R-squared	0.42	0.24	0.32	0.13	0.42	0.26	0.32	0.14	0.08	0.05	0.08	0.05	0.08	0.08	0.08	0.01
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	No	Yes	No
Sample	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All

Note: Profit Rate is the share of profits in total sales, TFP is the Solow residual. See the text for details. $\overline{S}_j$ is the simple average of MAX_j and $MOST_j$. Regressions with Profit rates as dependent variables have restricted sample to establishments between the 2^{nd} and 98^{th} percentiles of profit rate distribution. *, ** and *** denote 10%, 5% and 1% significance respectively.

Table C.8: Establishment Performance and Technology Sophistication across Sectors

	ln(Sales per worker)														TFP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
K_j	0.33***	0.43***	0.22***	0.27***	0.24***	0.27***												
	(0.04)	(0.04)	(0.05)	(0.06)	(0.03)	(0.04)												
H_j	0.54	1.13***	0.22	0.72***	0.19	0.71***												
	(0.38)	(0.43)	(0.21)	(0.20)	(0.13)	(0.14)												
$\overline{S}j$	0.71***	0.99***	0.55***	0.66***	0.47***	0.56***	1.11***	2.06***	0.64***	0.87***	0.58***	0.73***	0.13*	0.24***	0.08**	0.15***	0.15***	0.12**
	(0.15)	(0.13)	(0.06)	(0.07)	(0.06)	(0.07)	(0.15)	(0.19)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)	(0.04)	(0.03)	(0.05)	(0.05)
Constant	5.36***	3.19***	6.64***	6.44***	7.19***	7.09***	9.15***	5.75***	8.52***	9.13***	9.62***	10.14***	-0.21	-0.55***	-0.73***	-0.34***	-1.00***	-0.27**
	(0.67)	(0.31)	(0.46)	(0.64)	(0.35)	(0.39)	(0.57)	(0.42)	(0.18)	(0.21)	(0.16)	(0.14)	(0.27)	(0.18)	(0.09)	(0.10)	(0.09)	(0.11)
N	792	792	6292	6292	5593	5593	1178	1178	7952	7952	7536	7536	662	662	6021	6021	4589	4589
R-squared	0.71	0.58	0.48	0.33	0.39	0.21	0.62	0.40	0.40	0.18	0.30	0.10	0.18	0.03	0.13	0.01	0.08	0.01
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Sample	Agri.	Agri.	Manu.	Manu.	Serv.	Serv.	Agri.	Agri.	Manu.	Manu.	Serv.	Serv.	Agri.	Agri.	Manu.	Manu.	Serv.	Serv.

Profit Rate is the share of profits in total sales, TFP is the Solow residual. See the text for details. $\overline{S}_j$ is the simple average of MAX_j and $MOST_j$. Agri., Manu. and Serv. refer to the samples of establishments in agriculture, manufacturing and services 1-digit sectors. Regressions with Profit rates as dependent variables have restricted sample to establishments between the 2^{nd} and 98^{th} percentiles of profit rate distribution. Note: *, ** and *** denote 10%, 5% and 1% significance respectively.

Table C.9: Establishment Performance and Technology Sophistication across Countries

	ln(Sales per worker)						Profit Rate			TFP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
K_j	0.24***	0.11***	0.31***									
	(0.03)	(0.04)	(0.03)									
H_j	0.21**	0.53*	0.09									
	(0.11)	(0.29)	(0.10)									
$\overline{S}_j$	0.52***	0.46***	0.51***	0.62***	0.57***	0.63***	0.04***	0.07*	0.04***	0.11***	0.12	0.11***
	(0.05)	(0.10)	(0.05)	(0.05)	(0.08)	(0.05)	(0.01)	(0.03)	(0.01)	(0.03)	(0.08)	(0.03)
$\overline{S}_j$ * D(High-income)	-0.07			-0.06			0.02			0.01		
	(0.11)			(0.09)			(0.04)			(0.09)		
Constant	5.99***	11.21***	5.30***	8.40***	12.35***	8.24***	0.06	-0.07	0.08*	-0.78***	0.68***	-0.78***
	(0.31)	(0.61)	(0.30)	(0.32)	(0.27)	(0.38)	(0.04)	(0.11)	(0.05)	(0.10)	(0.24)	(0.10)
N	12677	1735	10942	16666	3366	13300	12206	2039	10167	11272	1366	9906
R-squared	0.42	0.34	0.38	0.32	0.22	0.25	0.08	0.02	0.12	0.08	0.16	0.07
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	High-income	Low-income	All	High-income	Poor Countries	All	High-income	Low-income	All	High-income	Low-income

Note: Profit Rate is the share of profits in total sales, TFP is the Solow residual. See the text for details. $\overline{S}_j$ is the simple average of MAX_j and $MOST_j$. $D(High-income)$ is a dummy variable that takes the value of 1 if country is high-income (South Korea, Poland and Croatia), and 0 otherwise. Regressions with Profit rates as dependent variables have restricted sample to establishments between the 2^{nd} and 98^{th} percentiles of profit rate distribution. *, ** and *** denote 10%, 5% and 1% significance respectively. For the profit rate, we drop the top and bottom 2%.

D Sector classification

Sector classification is an important feature of the FAT survey, given that SSBF modules apply only to firms belonging to these specific sectors. Moreover, the potential heterogeneity across firms and technologies within sectors led us to give special attention to this topic throughout the process, from designing the FAT questionnaire to implementing data collection and validating the results at a granular sectoral level.

Sector classification in the technology grid The sector-specific technology grid was designed following the International Standard Industrial Classification of all Economic Activities (ISIC). Most SSBF grid was designed the 2-digit ISIC sector definition, splitting up to 3-digit in some cases, such as agriculture and livestock. When defining the SSBFs and their respective technologies in the grid, we needed to manage the challenge of mapping specific business functions and technologies while making data collection feasible. Increasing the sectoral disaggregation and the number of strata usually requires larger sample sizes, with non-negligible implications in terms of cost and data collection challenges.

When discussing the grid with sector experts, we emphasize the importance of identifying business functions and their respective technologies that were broadly relevant across all firms that belong to that sector, disregarding the specific products they produce. Following these discussions, whenever needed, we made adjustments. For example, in agriculture, the functions of land preparation, irrigation, pest management, harvesting, storage, and packaging are relevant for both "non-perennial" (e.g., growing of cereal and vegetables) and "perennial crops" (fruits and nuts). Yet, these functions do not apply to "animal production," which is another group of activities (3-digit ISIC), for which we design another grid, "Livestock," including "Breeding, Feeding, Animal healthcare, Herd Management and Monitoring, and Transport," with the support of other sector experts. These categories of products belong to the 2-digit ISIC classification "Crop and animal production, hunting and related service activities." Therefore, the grid for "agriculture" and "livestock" was designed at the 3-digit level to ensure SSBFs and respective technologies were relevant for firms classified in these sectors. Another SSBF grid designed at the 3-digit level was "Banking." This was because we were mostly interested in "Monetary intermediation," provided by typical commercial banking.

For all other sectors, we kept the disaggregation at 2-digit ISIC. For example, in "Manufacture of food products" the business functions were broadly identified as relevant processes for the 14 classes of food products (4-digit ISIC) (e.g., Processing and preserving of meat, Manufacture of dairy products, Manufacture of bakery products). In "Manufacture of wear-

ing apparel," the functions "design, cutting, sewing, finishing, and fabrication" and their respective technologies were broadly identified as relevant for all groups (3-digit) and class of activities (4-digit), including Manufacture of wearing apparel, Manufacture of articles of fur, and Manufacture of knitted and crocheted apparel.

Sector classification of firms in the FAT survey In the FAT questionnaire, we have various questions to accurately define the firm's sector of activity. To start, our sampling frame provides the sector of activity of the establishments, which we use to stratify the sample. We have multiple questions to confirm this information and ensure that we have an updated status of the sector classification and the correct application of the sectoral module.

First, we have a screener questionnaire that was used to confirm the establishment's contact information and schedule the interviews. The screener asks the following question:

Q (S.5) What type of product or service represents this establishment's greatest share of annual sales? Based on the description of the main product or service, the firms were classified into sectors for which we have SSBF modules, "other manufacturing," or "other services," to prepare for the implementation of the SSBF module, and map the sectors according to 2-digit ISIC classification.

Second, when implementing the survey with the main manager, we asked a similar question, specifically about the last fiscal year, to trigger the module using the final sector classification.

Q. (A4) Over the year [LAS FISCAL YEAR], please tell me what type of product or service represents this establishment's greatest share of annual sales? For this question, we record the sector classification (Q.a5a) as a categorical variable (e.g., agriculture, livestock, food processing, etc.) plus the detailed description of the main activity and product (Q.a5b) in text format.

In addition, we programmed the survey to confirm "what sector-specific module should be used with the following conditions: If the sector is different from the original information provided in the screener questionnaire, this answer should be confirmed again to proceed.

With the information collected from the survey, combined with sector information from the sampling frame, we were able to define and classify firms up to 4-digit ISIC Rev. 4 definition.

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