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The Role of Technology in Reducing the Gender Gap in Productivity

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Abstract

This paper explores new firm-level data to examine the gender gap in technology adoption and the associated effect on firm performance. The data show a small difference in technology sophistication between firms managed by women and those managed by men, but there are larger differences in terms of labor productivity. Firms with female top managers are just as likely to adopt the most sophisticated technologies for general business functions that are common across all firms except for enterprise resource planning. However, firms managed by women adopt advanced technologies less frequently for sector-specific business functions. The study also finds that firms with higher technology sophistication tend to have higher productivity and the returns to the use of more sophisticated technologies are larger in businesses managed by women, which helps to narrow the productivity gap between firms managed by women and those managed by men.

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The Role of Technology in Reducing the Gender Gap in Productivity

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1 Introduction

Despite progress in female labor force participation, women encounter considerable barriers to breaking the *glass ceiling* and reaching high-level managerial positions. Even though women make up nearly 50 percent of the workforce in some regions, their representation decreases significantly in executive roles, with less than 5 percent of women holding top executive positions in the US and the LAC region (Flabbi et al., 2017). Beyond the social benefits of rising female participation in management, a sizable literature made a "business case for women leaders", emphasizing women's unique managerial style and contribution to firms' strategic choices and performance (Rosener, 1998; Ravasi and Schultz, 2006; Fernando et al., 2020; Hoobler et al., 2018).

A large literature has explored differences in performance between male- and female-managed businesses without reaching a consensus (Hoobler et al., 2018). Some studies suggest that female leadership is negatively related to firm performance (Allison et al., 2023; Lemma et al., 2023), while others observe a positive association (Moreno-Gómez et al., 2018; Flabbi et al., 2019) or even a non-significant impact (Dale-Olsen et al., 2013; Flabbi et al., 2019). These equivocal findings may be due to the inability to control for other mediating factors. Gender differences in firms' assets and labor market practices are significant (Allison et al., 2023; Inmyxai and Takahashi, 2012), and women are often disadvantaged when accessing credit, facing higher interest rates and lower loan approval rates (Chaudhuri et al., 2020; Muravyev et al., 2009). Also, gendered social norms not only prevent women from entering the labor market, but also deter the productivity of their businesses (Bose, 2022).

A key mediating factor is technology. Although extensive literature shows a positive relationship between technology and productivity and firm growth (Bartel et al., 2007; Juhász et al., 2020), little is known about how women in managerial positions affect technology adoption and use, as well as how these differences affect firm performance. This paper aims to shed some light on this critical issue by examining the disparities in technology adoption between businesses managed by women and men and studying whether these differences in technology adoption mediate the gender gap in firms' performance.

The upper echelon theory suggests that the characteristics of top managers, such as their age, gender, education, and experience, can influence organizational outcomes (Hambrick and Mason, 1984). Female top managers (FTM) may have different characteristics, values, and preferences compared to their male counterparts, and such differences can influence their decision-making regarding technology adoption. For instance, FTM tend to exhibit more risk aversion (Palvia et al., 2015) or prioritize collaboration and communication (Fernando et al., 2020), which can impact their choices of technology adoption. In addition, FTM may have a disadvantage relative to males in access to information (Inci et al., 2017) and financial resources (de Andrés et al., 2021), which may also affect their decisions to adopt and use technologies in their businesses.

To explore the links between technology and the gender gap in productivity, we leverage a comprehensive database from the Firm-level Adoption of Technology (FAT) survey conducted in 11 countries. In addition to productivity measures and information on top managers' gender, the FAT database offers a unique opportunity to explore technology adoption at the firm level and overcome a significant gap in the literature. For instance, most studies examining the technological gender gap have focused on gender ownership and a few technologies related to the agriculture sector (Hirpa Tufa et al., 2022; Teklewold et al., 2020; Doss and Morris, 2001) or on individual technologies such as internet connection (Allison et al., 2023) or e-commerce (Lashitew, 2023). In contrast, the FAT survey provides granular information on more than 300 technologies across almost 50 different business functions, allowing us to study the gender lens in various sectors and technologies.

Our results reveal a significant productivity gap between male- and female-managed establishments, with estimates ranging from 24 to 66 percent. Regarding technology adoption for general business functions, our analysis shows that female-managed enterprises are just as likely to adopt the most advanced technologies, except for Enterprise Resource Planning (ERP). In contrast, we find more significant differences in adopting advanced technologies associated with sector-specific business functions. Finally, the results show that technology adoption correlates positively with firm performance and that female management positively affects performance in more technologically sophisticated establishments.

Our analysis contributes to the expanding body of literature investigating the moderating factors influencing the gender gap in productivity. Specifically, the research by Allison et al. (2023) focuses on female ownership and finds that the negative association between female ownership and firm performance can be partially mediated by firms' access to finance, technology usage, and labor selection. The association between firm size and firm productivity varies between female and male-managed establishments. For instance, female-managed firms' disadvantage is only significant in small and medium enterprises (SMEs) (Fang et al., 2022). Our findings also align closely to Dezsö and Ross (2012), who suggest that the presence of female executives in senior management positions only deters firm performance in less innovative firms.

The findings of this study have several implications for policy makers. First, our results suggest that policies aimed at reducing the gender gap in technology adoption, particularly for sector-specific business functions, could effectively enhance firm productivity and competitiveness. This could involve targeted initiatives to support female-managed businesses in accessing and adopting more sophisticated technologies, including efforts to address the systemic barriers that hinder women's access to financial resources. Second, our results highlight the importance of technology in shaping the relationship between female management and firm performance, indicating that promoting technology adoption could effectively reduce the gender gap in firm performance.

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 describes the methodology used to identify the association between firms with female managers, performance, and technology. Section 4 provides descriptive statistics and initial correlations between female-managed firms and productivity as well as technology. Section 5 shows the main results and examines the role which these technological differences may have in explaining productivity differences. section 6 explains women's higher returns to the use of technology. section 7 explores the differences in the determinants of technology adoption between businesses managed by women and those managed by men. section 8 concludes with policy implications.

2 Data

Our study is based on the new data from the Firm-level Adoption of Technology (FAT) survey developed by Cirera et al. (2020). The survey was implemented in 11 countries, including both developing and developed economies. It includes a nationally representative random sample of firms with five or more employees in agriculture, manufacturing, and services. Our main dataset includes information on firms in advanced economies (the Republic of Korea, Poland, Georgia, and Chile), middle-income countries (Brazil,[1] Ghana, Kenya, Senegal, and Viet Nam), and low-income countries (Ethiopia and Burkina Faso).[2] Unlike most studies exploring the gender gap in general purpose technologies, the FAT survey offers detailed information on the adoption of several technologies across different business functions associated with general business or sector-specific business tasks.

2.1 Technology measure

The FAT survey covers over 300 technologies across almost 50 business functions, divided into general business functions (GBF) and sector-specific business functions (SBF). GBF

[1]In the case of Brazil, the survey is only representative for the state of Ceará.

[2]The survey was also implemented in India and Bangladesh. However, the survey in Bangladesh was implemented only for the firms in the manufacturing sector, and the survey in India excluded firms in agriculture and firms with fewer than 10 employees. Due to these differences in sample criteria and their correlation with women's participation, we have excluded these countries from our analysis.

includes seven business functions that are common to all firms, irrespective of sectors: (i) Business Administration, (ii) Production Planning, (iii) Sourcing and Procurement, (iv) Marketing and Customer Information, (v) Sales, (vi) Payment Methods, and (vii) Quality Control. For each GBF, the survey asks about a set of technologies, from the least to the most sophisticated. For instance, in Business Administration, the survey lists five different technologies from lower to higher level of sophistication, which include handwritten processes, computers with standard software, mobile apps, computers with specialized software, and enterprise resource planning (ERP). In contrast, SBF include 4 to 7 business functions specific to the 11 different sectors covered in the survey: i) Agriculture (Crops, Fruits, and Vegetables); ii) Agriculture (Livestock); iii) Food Processing; iv) Wearing Apparel; v) Leather; vi) Motor Vehicles; vii) Pharmaceuticals; viii) Retail and Wholesale; ix) Land Transportation; x) Banking; and, xi) Health Services.[3] Similar to GBF, the survey asks about relevant technologies to each SBF for each sector. For example, in the Wearing Apparel sector, the survey lists five different technologies to perform cutting processes: (i) manual cutting, (ii) cutting machine manually operated, (iii) semi-automatic cutting machine, (iv) automatic or computerized cutting machine, and (v) laser.

The survey provides a broad picture of a firm level adoption and more frequent use of technologies, capturing both the extensive and intensive margins. For each business function, the survey first inquires about which technologies a firm has adopted from a set of available technologies, representing the extensive margin. Then, the survey asks the firm to select the technology mainly (most frequently) used to conduct that business function, reflecting the intensive margin. For example, a business may report that it has adopted three technologies for Business Administration: handwritten processes, computers with standard software, and computers with specialized software. Among these three technologies, the business may indicate that it mainly uses computers with standard software to perform this business function.

Given the sizable number of business functions and technologies, we use technology indexes as summary measures for the sets of technologies. We construct four indexes based on the combination of each level of adoption (extensive and intensive margins) and each group of business functions (GBF and SBF). For each business function, we order technologies following the sophistication level and assign ranks from 1 to n, from least to most advanced. Because business functions include a different number of technologies, we first construct business function level sophistication measures by standardizing ranks so that the maximum rank is rescaled to 5 across business functions. Then, we construct firm-level technology indexes by averaging business function level indexes for both extensive and intensive margins

[3] SBF questionnaires are not asked for the firms operating in Other Manufacturing and Other Services

of GBF and SBF.[4]

The index varies from 1 to 5, in which 1 represents the use of the most basic technology, and 5 is the adoption of frontier technologies. In the example of Business Administration, a firm that adopts handwritten processes and computers with standard software will have a GBF index of 2 in the extensive margin. As the firm uses two technologies, the survey asks about the most used one. If the most used technology is handwritten processes, the GBF index at the intensive margin is 1. In contrast, if standard software, the intensive margin equals 2. Likewise, if a firm in the Wearing Apparel industry uses laser cutting, a frontier technology, as the most used technology, then it will have an SBF index of 5 at both extensive and intensive margins.

2.2 Identifying female-managed businesses

The FAT survey provides two variables that relate to gender participation in the management of a firm. The first variable indicates whether there are any females among the firm owners, while the second variable identifies whether the top manager is female. Although both variables are highly and significantly correlated (a coefficient of 0.5), the female ownership variable is substantially less precise, as the share of female ownership is not collected in several countries.[5] In contrast, the indicator of FTM shows less measurement errors and more precisely capture if females are involved in the management of firms.

The survey indicates that only 20% of firms are managed by women (Table 1), which is consistent with other findings in the literature. For instance, the World Bank Enterprise Survey reports that, for a representative sample of over 130,000 firms, about 16% are female-managed firms. Throughout the analysis, unless otherwise stated, we will refer to female establishments as those managed by female top managers.

The country income level is positively associated with female participation in top managerial positions. Table 1 shows the percents of firms with FTM for the various countries in

[4]See Cirera et al. (2020) for the detailed description of the technology indexes. The authors also provide several robustness checks for technology indexes using alternative cardinalizations.

[5]The survey includes information on ownership shares for Brazil, Senegal, and Viet Nam. Although the correlation coefficient between female participation in ownership and majority ownership (50% or more) by women is also high (0.56), there are large heterogeneities across sectors. For example, firms with any female owner in the Motor Vehicles sector is 73.4%, but only 3.2% has female owners with more than 50% of ownership share. Similarly, the share of firms with at least one female owner is almost three times higher than that with females having majority ownership (50% or more) in the Livestock and Crops sector, and two times higher than that in the Food Processing sector. The large gap between businesses with any female owner and female with 50% or more ownership is also observed in other studies. Using the World Bank Enterprise Survey, Lemma et al. (2023) examine the difference between these variables in Kenya and South Africa. They found that, in Kenya, 47.5% of firms have female participation in ownership, while only 13.2% are women-owned. In the case of South Africa, the gap is much smaller, with 10.6% of female participation in ownership and 8.7% of majority ownership by women.

our sample. In Korea, 36.8% of establishments are managed by women, while only 13.5% of establishments have FTM in Senegal and 12.8% in Ethiopia. Although Chile has a relatively higher income, only 14.1% of Chilean firms are managed by women. Nevertheless, the share of FTM firms is positively correlated with GDP per capita at the country level. This suggests that as country grows there are more female participation in management of businesses.

Table 1: Percent of firms with FTM by country

	Percent of firms with FTMs (%)	Observations
Korea, Rep.	36.84	1,520
Brazil	27.65	711
Viet Nam	25.77	1,499
Georgia	22.72	1,743
Poland	21.20	1,494
Kenya	16.54	1,297
Ghana	16.12	1,259
Chile	14.17	1,052
Burkina Faso	14.07	600
Senegal	13.47	1,785
Ethiopia	12.87	1,475
Total	19.44	14,435

Note: This table shows the percents of firms with FTMs across countries. Shares are weighted by sampling weights. Number of observations are unweighted. Data from the FAT surveys in 11 countries including Brazil, Burkina Faso, Chile, Ethiopia, Georgia, Ghana, Kenya, Korea, Rep., Poland, Senegal, and Viet Nam. FTM = Female Top Manager.

There is a large sectoral heterogeneity in the firms having female top managers. Table 2 presents the percents of the firms with FTM across sectors. The results show that while only 2.4% of establishments in Motor Vehicles have FTM, the share increases substantially in other sectors such as Food processing (33.4%), Health services (32.6%), and Leather and footwear (54%). That is, women are concentrated in some specific sectors for some reasons such as self-selection or some entry barriers including access to finance, education, management, etc., which are examined in later sections.

Table 2: Percent of firms with FTM by sector

	Percent of firms with FTMs (%)	Observations
Leather and footwear	54.01	188
Food processing	33.48	1,501
Health services	32.61	653
Financial services	31.59	452
Accommodation	26.17	605
Wearing apparel	20.97	934
Wholesale or retail	20.53	2,243
Agriculture - Crops	18.19	912
Pharmaceuticals	17.20	285
Other services	17.13	3,160
Other manufacturing	17.10	2,071
Land transportation	14.99	758
Livestock	13.35	385
Motor vehicles	2.40	288
Total	19.44	14,435

Note: This table shows the percents of firms with FTMs across industries.Shares are weighted by sampling weights. Number of observations are unweighted. Data from the FAT surveys in 11 countries including Brazil, Burkina Faso, Chile, Ethiopia, Georgia, Ghana, Kenya, Korea, Rep., Poland, Senegal, and Viet Nam. FTM = Female Top Manager.

2.3 Productivity and other covariates

To measure firm performance, we primarily focus on labor productivity, measured as the log of value added per worker. We take the log of the ratio of the difference between sales and the cost of intermediate goods and the number of employees. We convert values to US dollars using the Purchasing Power Parity (PPP) conversion from the World Bank.[6] In addition to labor productivity, the survey provides information on several firm and manager characteristics, including exporting and multinational status, management practices, firms' sector and region, and managers' education and experience in the sector (see Table B1 for summary statistics).

We convert some of firm and manager characteristics into three indexes, namely the *managerial quality index*, the *management human capital index*, and the *innovation and skill index*. First, the managerial quality index aggregates information on firms' managerial

[6]Due to confidentiality, information on labor productivity is not available for Chile and Poland in the FAT survey. Also, in the case of Burkina Faso, only 12 out of 80 firms with FTM provided information on both sales and intermediate costs. Therefore, our productivity analysis focuses on a smaller sub-sample excluding these three economies.

practices by taking two direct measures (formal incentives and performance indicators) and an indirect measure (non-family business).[7] Formal incentive and non-family business are dummy variables. Performance indicator is a categorical variable including four categories (none, 1-2, 3-9, 10 or more performance indicators), which is scaled between 0 and 1. We average three variables to construct the managerial index.

Second, the management human capital index focuses on managers' education and experience. Manager's education is a dummy variable for managers with a college degree. Manager's experience is a continuous variable normalized between 0 and 1.[8] Two additional variables include dummies for the manager who studied abroad and for the manager who have experience in a large company. We take the average of the four variables to estimate the management human capital index. Lastly, the innovation and skills index considers workers' education and firms' innovation. In particular, we take the share of college-educated workers, the share of R&D employees, and a dummy indicating whether the firm developed, customized, or significantly modified any equipment, machine, or software in the last three years. The share of college and R&D workers is normalized between 0 and 1. We average these three variables to construct the innovation and skills index.

3 Empirical strategy

3.1 Gap in labor productivity

The first set of questions we aim to answer is whether female-managed establishments are less productive than male-managed ones and whether we find differential productivity effects of the adoption of more advanced technologies between male- and female-managed firms. For this, we start with a simple specification, estimating a linear regression model of firm productivity on FTM, controlling for several key covariates. In particular, we run the following specification:

$$ln(VAPW)_i = \alpha_0 + \alpha_1 FTM_i + X_i' \gamma + \theta_r + \sigma_j + \epsilon_i \tag{1}$$

where $ln(VAPW)_i$ is the outcome variable, labor productivity measured as the logarithm of the value-added per worker, for a firm i. The FTM_i is a dummy variable for a firm having a female top manager. The vector X_i consists of a set of firm characteristics, including the logarithm of employment, the logarithm of capital per worker, formality, and the manage-

[7]Recent literature shows that family businesses adopt less advanced management practices Bloom and van Reenen (2010).

[8]We take 60 years as the maximum value to account for possible errors in data collection.

ment human capital index described in section 2. The specification also includes region (θ_r) and sector (σ_j) fixed effects.

The FTM_i is the main variable of interest, and the coefficient (α_1) captures the productivity gap between male- and female-managed businesses controlling for covariates. However, having a female top manager (FTM_i) is not randomly determined. Top managers with different genders may have different competencies and managerial styles and thus choose certain types of businesses. Also, firms with different business characteristics may look for different types of top managers. These may lead to self-section bias in our gender gap estimates.

To deal with the potential endogeneity issue in the estimates, we also estimate a two-stage least squares (2SLS) specification in addition to the OLS estimates. Following Allison et al. (2023), we use the share of other firms with female top managers in the same region (see also Flabbi et al., 2019) and the existence of women among the business owners as instrumental variables (IVs). The main assumption is that regions with more female-managed establishments are positively related with the likelihood of a firm having an FTM, but are not associated with the labor productivity of a firm. For instance, women would share less restrictive social norms in a given region, facilitating labor market participation and access to top managerial positions. Similarly, it is assumed that at least having one female owner in a firm would likely increase the chances of having an FTM, particularly in small companies where the owner is likely to be the top manager. Our first stage regression is specified as:

$$FTM_i = \mu_0 + \mu_1 ShareRegion_i + \mu_2 Owner_i + X_i'\gamma + \theta_r + \sigma_j + \epsilon_i \tag{2}$$

where $ShareRegion$ indicates the share of women-led firms in a given region (excluding the firm i), and $Owner$ is a dummy equal to one if firm i has at least one woman among the owners. The second stage is specified as follows.

$$ln(VAPW)_i = \delta_0 + \delta_1 F\hat{T}M_i + X_i'\gamma + \theta_r + \sigma_j + \epsilon_i \tag{3}$$

where $F\hat{T}M_i$ indicates the predicted value for FTM for a firm i. To get the correct standard errors, we estimate both specifications together.

In addition to estimating the gender gap in productivity, we examine the role of technologies in this productivity gap. Particularly, we investigate if the impact of technologies on productivity varies between male- and female-managed businesses. For this, we use Equation 1 and add the interaction term between technology and FTM. The regression is specified as:

$$ln(VAPW)_i = \beta_0 + \beta_1 FTM_i + \beta_2 Tech_i + \beta_3 Tech_i FTM_i + X_i'\gamma + \theta_r + \sigma_j + \epsilon_i \tag{4}$$

where $Tech_i$ is one of the four technology indexes including extensive GBF, intensive GBF, extensive SBF, and intensive SBF. The $Tech_iFTM_i$ is the interaction between FTM indicator and technology indexes. Because the technology indexes vary between 1 and 5, we demean these indexes so that we can interpret the coefficient of technology indexes for the firms with the average technology indexes.

3.2 Oaxaca-Blinder and differences in technology adoption

To further examine the relative contribution of differences in endowments to the gender gap in technology adoption and use, we apply the Oaxaca-Blinder decomposition method. Specifically, we estimate the twofold Oaxaca–Blinder decomposition using the following specification:

$$\overline{T}^F - \overline{T}^M = \overbrace{[(\overline{X}^F - \overline{X}^M)'\hat{\beta}^*]}^{\text{Explained}} + \overbrace{[(\overline{X}^F)'(\hat{\beta}^F - \hat{\beta}^*) + (\overline{X}^M)'(\hat{\beta}^* - \hat{\beta}^M)]}^{\text{Unexplained}} \quad (5)$$

where $\overline{T}^g$ is the average technology sophistication for firms managed by different gender group g of top managers, which is either female (F) or male (M). $\overline{X}^g$ is the set of endowments (or factors), which include managerial quality index, management human capital index, innovation and skills index, firm size, multinational, exporting status, government support, interaction MNEs, and sector dummies. $\hat{\beta}^*$ is the set of coefficients of factors from the pooled regression with a dummy for FTM, while $\hat{\beta}^g$ is a vector of the coefficients from separate regressions for each gender group g. To focus on the within country endowments, we first remove between country variations by estimating residuals from linear regressions of each variable with country dummies. We use the normalization procedure developed by Yun (2005) on the categorical variables so as to prevent the selection of the omitted base variable from arbitrarily influencing the unexplained portion of the decomposition.

The raw mean difference in technology sophistication of firms with female and male top managers $(\overline{T}^F - \overline{T}^M)$ is decomposed to two components: "Explained" and "Unexplained." The first component $(\overline{X}^F - \overline{X}^M)'\hat{\beta}^*$ shows the part of the technology differences explained by gender differences. The second component is the unexplained part that captures the differential effects of factors for each gender group. This is often considered as discrimination, but it also reflects differential effects of unobserved variables that are not included in the analysis.

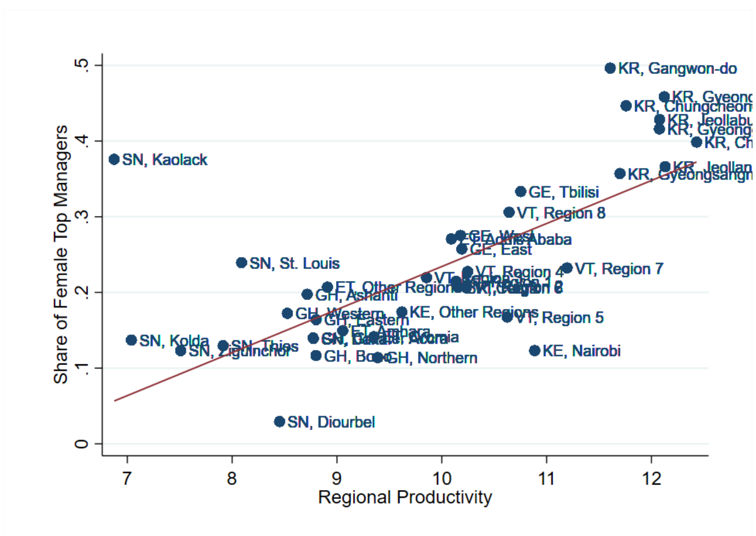
4 Descriptive statistics

Before investigating the gender gap in productivity and the role of technologies, we first analyze differences in female participation in top management positions across regions and how female-managed establishments differ in some important aspects.

4.1 Performance and the characteristics of firms and managers

As discussed in Section 2, Table 1 indicates that the percent of firms with FTM correlates with GDP per capita. We examine this association using regional variations. Figure 1 takes the averages of labor productivity (measured as the log of value added per worker) for different regions and plots these against the shares of firms with FTM at the regional level. The scatter plot shows that regional labor productivity is positively correlated with the regional share of firms with FTM. In low-productive regions like Diourbel in Senegal, less than 10% of firms have FTM, while in high-productive regions in Korea, the share is substantially larger.[9]

Figure 1: Correlation between regional productivity and the share of FTM



Note: The regional productivity is measured as the average value added per worker based on a representative sample of the FAT data for each region, using sampling weights. Countries are as follows: Brazil (BR); Burkina Faso (BF); Ethiopia (ET); Georgia (GE); Ghana (GH); Kenya (KE); Korea, Rep. (KR); Senegal (SN); and Viet Nam (VT). Data on labor productivity is not available for Poland and Chile.

Table 3 shows the descriptive statistics of labor productivity and other covariates by all, male, and female sample (columns 1 to 6). It also provides the differences between male- and

[9]We regress firm productivity on sector and regional fixed effects and controlling for size group dummies. Average sector and region productivity are hence equal to the respective fixed effects.

female-managed businesses of these variables (columns 7 to 9). The seventh column shows the unconditional difference; the eighth column presents the differences after controlling for country fixed effects; and the last column shows the differences controlling for sector and firm size in addition to country fixed effects.[10]

The average firm in our sample has about 41 employees, and 11% are multinationals, 13% are exporters, and 12% have received government support for adopting advanced technologies. Also, 61% of managers are college educated, 12% have studied abroad, and on average, they have more than 18 years of experience in the sector. 68% of establishments provide formal incentives to their workers, but only 32% use performance indicators in their management practices. Moreover, most establishments are family businesses (91%), and only 20% developed, customized, or significantly modified any equipment, machine, or software in the last three years. This is in line with the small share of R&D employees (7%) and college-educated workers (26%).

The unconditional difference in labor productivity is negative, but the magnitude of the difference is small and insignificant (column 7). However, when we remove between-country variations and focus on within-country variations, there is a large and statistically significant gap in labor productivity between male- and female-managed businesses (column 8). Female-managed firms are 35% less productive than male-managed firm.[11] Additional estimates using region, size, and sector show similar labor productivity differences between male- and female-managed businesses (column 9). These results suggest that the small gender gap in labor productivity is primarily driven by the country composition and not the sector composition.

Firms with FTM also differ in many other aspects. They are less likely to export, interact with MNEs, and be multinationals. Interestingly, we do not find a statistically significant difference in firms' size and the likelihood of studying abroad. In contrast, we find that female managers have less experience in the sector and large companies. Moreover, male-managed companies are more likely to innovate and, on average, have a larger share of college-educated and R&D employees. Female-managed establishments have lower management human capital and innovation and skills indexes.

[10]Given the large share of FTM in Korea, and the fact that Korea has the highest levels of technological sophistication, it is important to at least partially correct for the country composition.

[11]The effect of an FTM on the logarithm of labor productivity is measured as (exp(-0.44) - 1)*100.

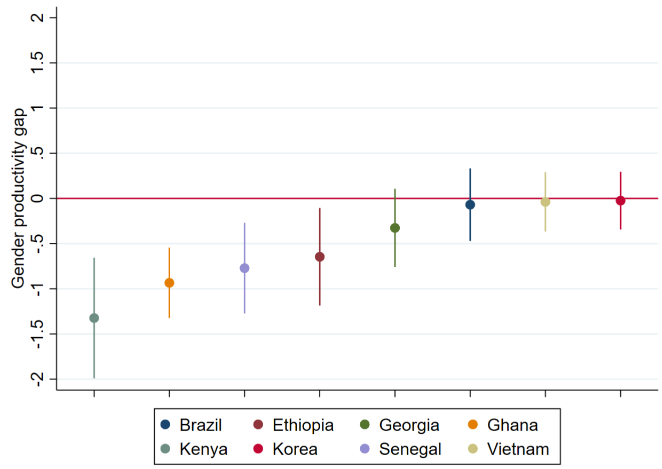
Table 3: Differences between male and female-managed businesses

	All		Male		Female		Difference		
	Mean	SD	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(VAPW)	10.03	2.23	10.04	2.21	9.99	2.41	-0.06	-0.44***	-0.44***
Number of employees	40.98	286.74	42.41	299.62	35.51	214.83	-6.90	-6.98	-9.20
Multinational	0.11	0.31	0.12	0.32	0.09	0.30	-0.03**	-0.02**	-0.02**
Exporter	0.13	0.33	0.13	0.33	0.11	0.34	-0.02*	-0.03***	-0.03***
Interaction with MNEs	0.24	0.42	0.25	0.42	0.20	0.42	-0.05***	-0.04**	-0.03*
Government support	0.12	0.32	0.11	0.31	0.13	0.36	0.02	0.00	0.00
Managerial quality index	0.36	0.24	0.37	0.23	0.34	0.26	-0.03***	-0.01	-0.02*
Non-Family company	0.09	0.28	0.09	0.27	0.10	0.31	0.01	-0.01	-0.01
Formal incentives	0.68	0.47	0.69	0.45	0.65	0.51	-0.04**	-0.00	-0.00
Performance indicators	0.32	0.30	0.33	0.29	0.27	0.31	-0.06***	-0.02**	-0.03***
Management human capital index	0.30	0.23	0.30	0.23	0.30	0.23	-0.00	-0.02*	-0.01
Manager's with college	0.61	0.49	0.60	0.48	0.66	0.51	0.06***	0.02	0.03
Manager's experience (years)	18.27	14.60	18.42	14.11	16.61	15.03	-1.81***	-2.36***	-2.23***
Experience in large company	0.21	0.41	0.22	0.40	0.17	0.40	-0.04**	-0.04**	-0.03
Studied abroad	0.12	0.33	0.12	0.32	0.12	0.34	-0.01	-0.01	-0.01
Innovation and skills index	0.18	0.24	0.18	0.23	0.18	0.25	-0.00	-0.02**	-0.02**
Share of college-educated employees	0.26	0.32	0.25	0.31	0.29	0.35	0.04**	-0.03*	-0.03*
Share of R&D employees	0.07	0.17	0.08	0.17	0.06	0.18	-0.02*	-0.02**	-0.02**
Innovation	0.20	0.40	0.21	0.40	0.16	0.39	-0.05***	-0.04***	-0.04**

Note: Table shows averages for baseline using sampling weights. The seventh column presents the unconditional difference, the eighth column presents the coefficients of linear regressions of each variable on female top management controlling for country, and the ninth column adds sector and size group dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The large and statistically significant gap in labor productivity is far from homogeneous across economies. Figure 2 illustrates the productivity gap between female and male-managed enterprises for each country in our sample. We find that the productivity gap between male and female-managed businesses is substantial in lower-income economies, but not statistically significant in higher-income countries. In Kenya, female-managed firms are about 77% times less productive. In Ghana, female-managed firms are 60% less productive, and in Ethiopia and Senegal, the difference is about 50%. In contrast, the gender gap in labor productivity becomes considerably smaller and insignificantly different from zero in Georgia, Brazil, Korea, and Viet Nam. These findings suggest that female-managed businesses can catch up during economic growth.

Figure 2: Gender gap in productivity by country



Note: Figure presents coefficients for individual country regressions of the logarithm of labor productivity on a dummy of female top managers, controlling for sector and size group dummies and using sampling weights. Vertical bars show estimated 95% confidence interval.

4.2 Technology adoption and use

We now turn to a descriptive statistics of technology adoption. Table 4 summarizes the extensive margin of technology adoption associated with the seven general business functions described in Section 2.1. The first four columns detail each group's mean and standard deviation, and the last three columns present the unconditional and conditional differences in the mean. The fifth column presents the unconditional difference, and the sixth column presents the linear regression coefficients controlling country fixed effects. The last column adds sector and size dummies. For each business function, we present information on the most sophisticated technologies in rows. For instance, in the case of Business Administration, specialized software and ERP are the most advanced ones.

The first notable finding for all general business functions is that few firms adopt the most advanced technologies. For instance, less than 4% of firms have adopted automated systems for quality control, and less than 2% use big data or machine learning for marketing.[12] Interestingly, we find that unconditional differences of technology adoption between male- and female-managed establishments are mostly negligible, except for online payment and virtual or cryptocurrency. In the case of most business functions, coefficients are not statistically different from zero. Yet, when we make the differences conditional on country in column 6 or region, size, and sector in column 7, we find that female-managed firms do

[12] Given the scope of this paper, we do not discuss country or sectorial differences in technology adoption. We refer the reader to a series of documents that explored these themes, including several country notes and a flagship report. See for instance, Cirera et al. (2021), Cirera et al. (2023), and Cirera et al. (2022).

not commonly adopt ERP for business administration and production planning as male-managed establishments. In the Appendix, Table B2 shows the descriptive statistics for the intensive margin. Similarly, differences are mostly minor, and few are statistically different from zero. The difference in the (intensive) use of ERP remains statistically significant and increases in the case of online payment.

Table 4: Difference in technology adoption between female and male top managers for GBF at the extensive margin

	Male		Female		Difference		
VARIABLES	Mean (1)	SD (2)	Mean (3)	SD (4)	Uncond. (5)	Cond. (6)	Cond. (7)
Business Administration							
Computers with specialized software	0.36	0.47	0.38	0.52	0.02	-0.03*	-0.03
Enterprise Resource Planning (ERP)	0.11	0.31	0.10	0.32	-0.01	-0.03**	-0.03**
Production Planning							
Specialized software for production	0.19	0.38	0.17	0.40	-0.01	-0.02	-0.01
Enterprise Resource Planning (ERP)	0.09	0.29	0.10	0.32	0.00	-0.02*	-0.02**
Supply Chain Management							
Supplier Relation Management (SRM)	0.06	0.24	0.06	0.25	-0.01	-0.00	-0.00
Supplier Relation Management (SRM) integrated	0.06	0.23	0.05	0.22	-0.01	-0.01	-0.01
Marketing							
Customer Relationship Management software (CRM)	0.08	0.27	0.07	0.28	-0.01	-0.01	-0.01
Big data Analytics or Machine learning	0.02	0.13	0.01	0.12	-0.01	-0.00	-0.00
Sales Methods							
External digital platforms	0.06	0.23	0.06	0.26	0.00	-0.00	-0.00
Online sales (e-commerce) using its own website	0.12	0.32	0.14	0.37	0.02	0.01	0.01
Electronic orders integrated to SCM system	0.06	0.23	0.06	0.26	0.00	-0.00	-0.00
Payment Methods							
Online or electronic payment through a bank wire	0.46	0.49	0.49	0.53	0.03	-0.04*	-0.03
Online payment through platform	0.31	0.45	0.24	0.45	-0.07***	-0.00	-0.00
Virtual or Cryptocurrency	0.00	0.06	0.00	0.04	-0.00**	-0.00*	-0.00*
Quality Control							
Statistical process control	0.15	0.35	0.15	0.38	-0.00	0.00	0.01
Automated systems	0.03	0.16	0.04	0.21	0.01	0.01	0.01

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also look at the adoption of sector-specific technologies for four sectors - Agriculture, Food Processing, Wearing Apparel, and Retail sectors in Appendix Tables B3, B4, B5, and B6. For instance, in the Agriculture sector, female-managed establishments are less likely to adopt advanced precision agriculture for pest control and advanced technologies for storage. For the Wearing Apparel sector, differences are statistically significant only for technologies associated with design, in which fewer female-led establishments adopt CAD. Interestingly, we find minimum to no difference in the Retail sector. Besides search engine marketing, male- and female-managed firms use very similar technologies. We see a clear gap in the adoption of cutting-edge technologies in the Food Processing sector. FTM are 5 percent less likely of adoption computer testing for input testing. In addition, we observe large differences in adopting power equipment controlled by computers or robotics for packaging.

Given a large number of technologies across several business functions, we summarize the overall technological sophistication using four different technology indexes. Table 5 provide the descriptive statistics of technology indexes and the differences of these indexes between male- and female-managed businesses. The unconditional differences in technology indexes are positive, but when countries are controlled the coefficients become negative, but the differences are insignificant. This may be because in some countries a large share of male-managed businesses rely on less sophisticated of technologies. When region, size, and sector are controlled, we find female-managed businesses tend to adopt similar level of GBF technologies, but less sophisticated SBF technologies.

Table 5: Difference in technology indexes between male- and female-managed firms managers

	Male		Female		Difference		
	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GBF - EXT	2.34	0.83	2.39	0.85	0.06*	-0.04	-0.03
GBF - INT	1.77	0.62	1.86	0.68	0.09***	-0.03	-0.02
SBF - EXT	2.09	0.98	2.18	1.04	0.08	-0.04	-0.09**
SBF - INT	1.64	0.72	1.70	0.76	0.06*	-0.03	-0.07**

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Results

5.1 Baseline

The descriptive statistics show that a significant gender gap in productivity exists after controlling for region, sector, and size. However, the conditional gender gap may still reflect other factors. To understand the gender gap in productivity, Table 6 presents the results from estimating Equation (1). Column (1) presents a simple specification without including any capital or technology-related covariates. Column (2) adds the management human capital index, and column (3) includes the logarithms of capital per worker and total employment.

Columns (4) to (7) add the different technology indexes. The results indicate that firms with FTM have lower labor productivity, which is consistent with our initial descriptive statistics and other findings in the literature (Allison et al., 2023).

Column (1) shows that firms with FTM are, on average, 38.4% less productive than their male counterparts. As we control for management human capital in column (2), the gap reduces slightly, in line with the small differences in FTM education and experience. Furthermore, the gap reduces significantly as we control for capital stock and technology in our specifications, highlighting the significant capital gap between men- and women-managed firms. For instance, in column (4), the difference in labor productivity between male- and female-managed establishments is 25.8%, a reduction of over 10 percentage points compared to column (1). The results also suggest that adopting and intensively using advanced technologies linked to GBF positively correlate with firm productivity. In the case of SBF, the association between labor productivity and technology seems weaker and only significant at the extensive margin.

Table 6: OLS estimates of productivity and technology gaps

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)	(5) Ln(VAPW)	(6) Ln(VAPW)	(7) Ln(VAPW)
Female Top Manager	-0.485*** (0.0880)	-0.458*** (0.0885)	-0.309*** (0.0968)	-0.302*** (0.0972)	-0.296*** (0.0969)	-0.281** (0.129)	-0.284** (0.130)
Log(Capital per worker)			0.276*** (0.0282)	0.256*** (0.0272)	0.265*** (0.0279)	0.258*** (0.0413)	0.259*** (0.0420)
Log(Employment)			-0.0470 (0.0391)	-0.117*** (0.0402)	-0.0941** (0.0410)	-0.0889 (0.0544)	-0.0613 (0.0526)
GBFs - Extensive margin				0.285*** (0.0606)			
GBFs - Intensive margin					0.382*** (0.0834)		
SBFs - Extensive margin						0.146** (0.0652)	
SBFs - Intensive margin							0.115 (0.0895)
Formality	2.215*** (0.156)	1.987*** (0.167)	1.726*** (0.182)	1.662*** (0.183)	1.622*** (0.183)	1.771*** (0.229)	1.791*** (0.228)
Management human capital index		0.683*** (0.193)	0.554** (0.218)	0.292 (0.222)	0.365* (0.217)	0.210 (0.321)	0.245 (0.325)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8579	8579	6717	6717	6717	4370	4362
R-squared	0.342	0.346	0.488	0.495	0.494	0.500	0.495

Note: This table presents the OLS regression results. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. Estimates were performed using sample weights. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7 shows the 2SLS model results using the regional share of FTM and female ownership as instrumental variables. First-stage F statistics are much higher than 10, which indicates the high relevance of the excluded exogenous variables for all specifications. In addition, Sargan's overidentification test shows that the combination of the two IVs is valid for all specifications. Although qualitatively similar to the OLS estimates, the IV coefficients are larger in general, thus suggesting a more substantial gap between male- and female-managed establishments. For instance, in columns (3) and (4), we observe a gap of 43% and 44%, respectively. In Appendix Tables C1 and C2, we control sector-by-region fixed effects to compare firms hiring different genders of managers in the same economic environment. The results are qualitatively similar to those in Tables 6 and 7. However, given the smaller number of observations in some sector-by-region cells, we use this specification as a robustness check for our main results.[13]

Table 7: Two-Stages Least Squares

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)	(5) Ln(VAPW)	(6) Ln(VAPW)	(7) Ln(VAPW)
Female Top Manager	-1.081***	-1.074***	-0.567***	-0.587***	-0.502**	-0.595**	-0.561**
	(0.216)	(0.217)	(0.210)	(0.210)	(0.210)	(0.275)	(0.278)
Log(Capital per worker)			0.274***	0.253***	0.264***	0.253***	0.255***
			(0.0269)	(0.0259)	(0.0268)	(0.0382)	(0.0386)
Log(Employment)			-0.0450	-0.115***	-0.0917**	-0.0843*	-0.0572
			(0.0364)	(0.0376)	(0.0382)	(0.0493)	(0.0476)
GBFs - Extensive margin				0.286***			
				(0.0560)			
GBFs - Intensive margin					0.380***		
					(0.0773)		
SBFs - Extensive margin						0.138**	
						(0.0602)	
SBFs - Intensive margin							0.103
							(0.0806)
Formality	2.258***	2.074***	1.766***	1.706***	1.660***	1.810***	1.826***
	(0.152)	(0.166)	(0.173)	(0.174)	(0.174)	(0.213)	(0.213)
Management human capital index		0.562***	0.488**	0.226	0.309	0.159	0.201
		(0.197)	(0.214)	(0.215)	(0.211)	(0.303)	(0.307)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8423	8423	6627	6627	6627	4317	4309
R^2	0.333	0.335	0.486	0.493	0.493	0.497	0.493
F	163.2	163.5	124.2	124.7	125.6	68.76	66.35
J	0.0273	0.0569	0.00182	0.00860	0.00625	0.0312	0.0272

Note: This table presents the 2SLS regression results. Exclusion restrictions are the regional share of FTM and female ownership. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. Estimates were performed using sample weights. Robust standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

[13] One concern in these linear regression analyses is that female top managers are not randomly allocated across the firms. To reduce some bias from self-selection, we also estimate the same specifications using a propensity score matching method in Appendix D. Overall, the results are qualitatively similar.

5.2 Role of technology in the gender gap in performance

We then turn to the interaction between firm performance and technology adoption to examine how technology can mediate the gender productivity gap. Table 8 shows the estimates based on Equation 4. In addition to a productivity gap for firms with FTM, Table 8 shows substantial gender differences in the effects of technology adoption at the intensive margin on firm productivity. These findings suggest that although there is a gender gap in firm productivity, this gap decreases as firms adopt more sophisticated technologies, such that firms with FTM benefit more from advanced technologies.

Table 8: OLS estimates of productivity and technology gaps

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)
Female Top Manager	-0.298*** (0.0977)	-0.282*** (0.0966)	-0.283** (0.129)	-0.283** (0.128)
GBFs - Extensive margin	0.268*** (0.0670)			
FTM*GBF EXT	0.104 (0.128)			
GBFs - Intensive margin		0.290*** (0.0943)		
FTM*GBF INT		0.428*** (0.145)		
SBFs - Extensive margin			0.131* (0.0717)	
FTM*SBF EXT			0.0829 (0.146)	
SBFs - Intensive margin				0.0665 (0.0946)
FTM*SBF INT				0.294 (0.203)
Controls	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Observations	6717	6717	4370	4362
R-squared	0.495	0.496	0.501	0.497

Note: All estimates control for capital stock, employment, sector, country, and additional controls, including formality and the management human capita index. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. Estimates were performed using sample weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9 provides additional results from the 2SLS model estimates. As we include interaction terms between FTM and technology in our baseline model, we have two endogenous variables: FTM and the interaction between FTM and technology index. For the interaction terms, we use the interaction between technology and the exogenous variables ($Share$ and $Owner$) as our additional instruments. The magnitudes and patterns of the coefficients from Table 9 are qualitatively similar to those from our original OLS estimates, indicating large and positive effects for the interaction terms associated with GBF and SBF at the intensive margin. Furthermore, all coefficients for the interaction terms in the 2SLS specification are statistically different from zero. As a robustness check, we also estimate the 2SLS specifications with sector-by-region fixed effects in the Appendix Tables C3 and C4 and found the results are qualitatively similar. Together, the results suggest that although there is a gender gap in firm productivity, this gap decreases as firms adopt more sophisticated technologies, such that firms with FTM benefit more from advanced technologies.

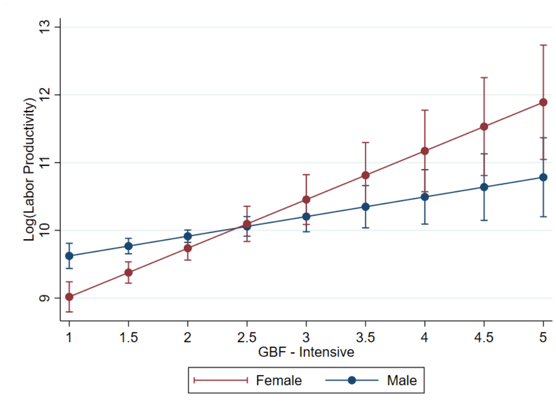
Table 9: 2SLS estimates for the interaction between productivity and technologies

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)
Female Top Manager	-0.431* (0.230)	-0.372* (0.212)	-0.575** (0.278)	-0.576** (0.282)
GBF EXT	0.154* (0.0840)			
FTM*GBF EXT	0.776** (0.343)			
GBF INT		0.177 (0.113)		
FTM*GBF INT		0.955*** (0.323)		
SBF EXT			0.0173 (0.0920)	
FTM*SBF EXT			0.673* (0.358)	
SBF INT				-0.0236 (0.110)
FTM*SBF INT				0.774* (0.444)
Controls	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Observations	6627	6627	4317	4309
R^2	0.483	0.493	0.487	0.491
Shea's R-squared	0.173	0.186	0.185	0.182
Shea's R-squared	0.118	0.187	0.117	0.176
J	0.238	0.0589	0.0376	0.00309

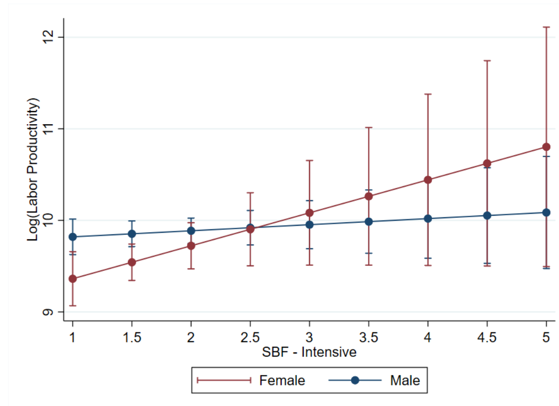
Note: This table presents the 2SLS regression results. Exclusion restrictions are the regional share of FTM and female ownership and the interaction of each variable with the technology indexes. All estimates control for capital stock, employment, sector, country, and additional controls, including formality and the management human capita index. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates were performed using sample weights. Robust standard errors are in parentheses.

Figure 3 shows the marginal effects of technology on labor productivity by different levels of technology sophistication for women and men-managed businesses based on our 2SLS estimates. Panel (a) displays the marginal effects associated with the sophistication of GBF technologies, while Panel (b) shows the impact of the sophistication of SBF technologies. Our findings indicate that women-managed businesses tend to experience lower productivity returns from technologies than men-managed businesses when technology sophistication is low. However, they begin to catch up with the productivity of male-managed firms as the technology sophistication level increases. That is, the higher returns to the use of technology for women-managed businesses increase with the digitalization of most business functions. These patterns hold true for both GBF and SBF technologies and suggest that the intensive use of more sophisticated technologies helps women-managed businesses to reduce the productivity gap.

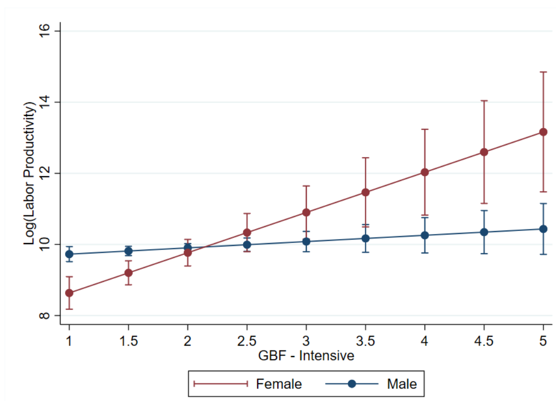
Figure 3: Returns to technology use by gender



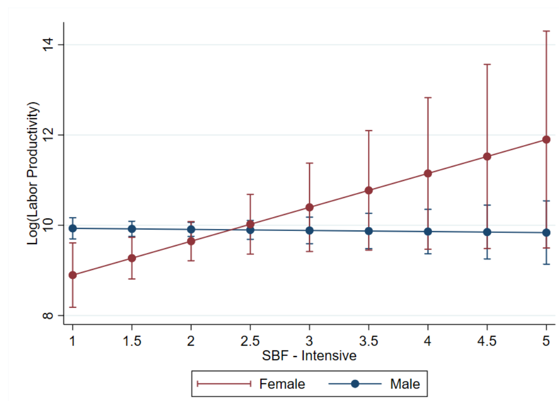
(a) GBF technologies, OLS



(b) SBF technologies, OLS



(c) GBF technologies, 2SLS



(d) SBF technologies, 2SLS

Note: This figures presents predicted values of the logarithm of labor productivity for firms with and without FTM at different values of the GBF and SBF technology indexes at the intensive margin. Panels (a) and (b) are based on OLS estimates and panels (c) and (d) are based on 2SLS regressions with the regional share of FTM and female ownership as exogenous variables. In addition, estimates control for sector and region fixed effects, formality, the logarithm of capital per worker, the logarithm of employment, and the management human capital index. Vertical bars show estimated 95% confidence interval. All estimates employ sampling weights.

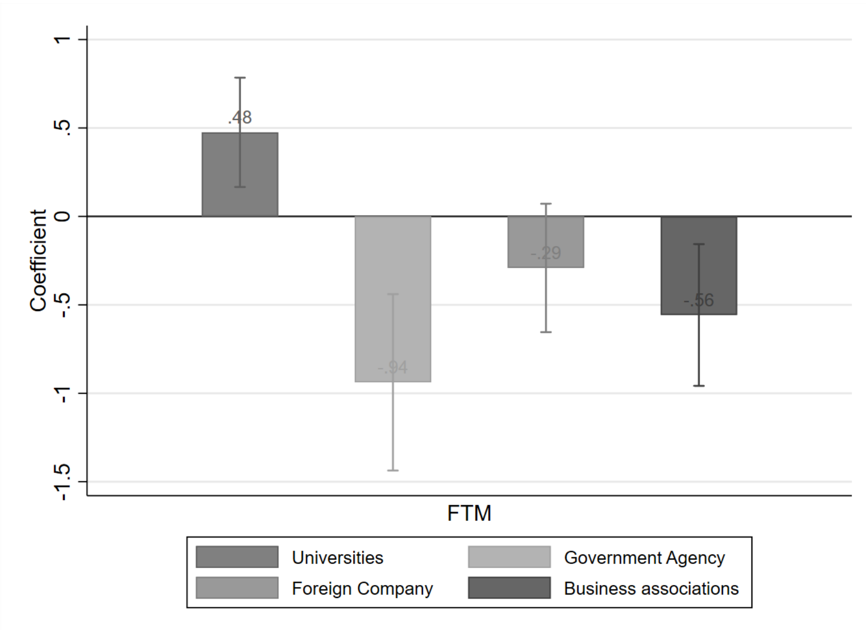
6 Explaining women's higher returns to the use of technology

Understanding FTM's higher returns to technology adoption is critical for policy. In this section, we describe some tentative channels based on available data. The first possible channel is the link between women's managerial style and their capacity to optimize technology adoption. For instance, women's collaborative managerial style (Rosener, 1998) can facilitate employees' willingness to adopt new technologies and use them productively. Atkin et al. (2017) show that workers can be reluctant to adopt new production methods when incentives are misaligned within firms. Workers can resist adoption in various ways, including by misinforming owners about the value of the technology. Women are more likely to encourage participation by soliciting input from others and keeping open communication channels with their subordinates (Rosener, 1998; Dezsö and Ross, 2012), thus easing workers' reluctance to use the technologies in the production process productively.

The second potential channel can relate to FTM's more frequent interactions with universities, suppliers, and buyers, which can strengthen the adoption of certain technologies. For example, in the first wave of the FAT survey in Brazil, Viet Nam, and Senegal, firms were asked about the primary source of external consultants or organizations the establishment used to aid in adopting and using new machines. Figure 4 shows that FTM are substantially more likely to interact with universities when adopting new technologies while less likely to rely on government agencies and business associations. Furthermore, when searching for information about new technologies, Figure 5 shows that FTM are more likely to interact with suppliers and buyers to make decisions. This access to external knowledge can be critical in adjusting the new technologies to the business functions of the firm.

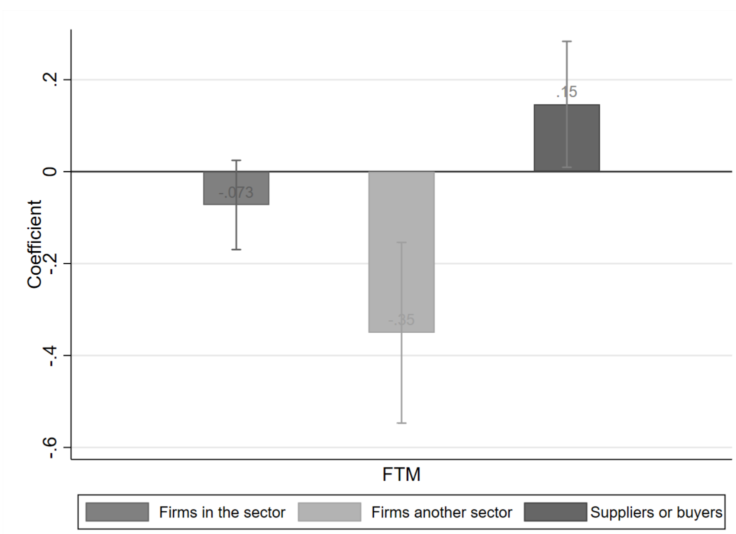
A third potential channel relates to how technology allows women to overcome many social barriers. Women are often responsible for juggling multiple roles, which requires a high level of organizational skills and efficient use of time, which digital technologies can help. For instance, in many countries, women still face restrictions on mobility, meaning that they must operate from home (Bose, 2022). In addition, during the COVID-19 pandemic, evidence suggests that female-managed businesses were particularly harmed by the fact that women needed to balance work with other domestic responsibilities. In this perspective, digitalization has an important role in fostering flexibility in the workplace, thus allowing women to combine entrepreneurial roles with various forms of caring responsibilities, which women generally carry out (Kamaha Njiwa et al., 2023), especially in small businesses.

Figure 4: Main source of external consultants



Note: This figure shows the predicted probability of using each source of external consultants and 90% confidence intervals from Probit regressions with controlling for country, sector, formality, and size. The information was available only for Brazil, Senegal, and Viet Nam. All estimates are weighted by sampling and country weights.

Figure 5: Main source of information



Note: This figure shows the predicted probability of using each source of information and 90% confidence intervals from Probit regressions with controlling for country, sector, formality, and size. All estimates are weighted by sampling and country weights.

7 Differences in the determinants of technology adoption between male- and female-managed businesses

The results in the previous section suggest that technology plays an important role in narrowing differences in productivity between male- and female-managed businesses. In other words, the contribution of the use of more sophisticated technologies on labor productivity is larger in firms with FTMs, even though female-managed firms are marginally less likely to adopt advanced technologies than male-managed ones. One option for policies that try to narrow this gender gap is to incentivize the adoption of more sophisticated technologies in female-managed firms. While technological upgrading is a continuous process (Cirera et al., 2022) and it is not realistic nor desirable that firms with FTMs adopt frontier technologies when capability or capital intensity do not complement advanced technologies, the results above suggest that incremental increases in technology sophistication can help reduce this productivity gap.

To this end, a critical element to designing these technology upgrading programs is understanding the factors contributing to adopting advanced technologies and how they differ between female and male-managed establishments. Table 10 presents the results of a Oaxaca-Blinder decomposition for each technology index (Table B7 and table B8 in the Appendix show the OLS estimates). To account for country differences, we replace the technology indexes with the residuals of a linear regression of each index on a set of country dummies. The results indicate that firms with the FTM adopt and use less advanced technologies, although the coefficients for the difference are not statistically significant. Differences in endowments explain 60% of the gap for the extensive margin and 67% for the intensive margin, with the remaining portion explained by the "structural" component. As for differences in "endowments", the decomposition shows that firms with FTM present lower managerial quality and are less likely to receive government support. These two components explain most of the gap in the explained portion. Other characteristics, such as exporters and multinationals have little power in explaining the differences in the technology adoption gap. As for the "structural" component, although most coefficients are not statistically different from zero, it is interesting to note that the coefficient for government support is negative and statistically significant for SBFs. Not only FTM are less likely to receive government support for technology adoption, but also less likely to benefit from it.

Table 10: Oaxaca-Blinder decomposition

	(1) GBF-EXT	(2) GBF-INT	(3) SBF-EXT	(4) SBF-INT
FTM	-0.026	-0.028*	-0.038	-0.032
	(0.023)	(0.017)	(0.035)	(0.023)
MTM	0.005	-0.001	-0.006	-0.008
	(0.013)	(0.009)	(0.019)	(0.013)
Difference	-0.031	-0.027	-0.032	-0.023
	(0.027)	(0.019)	(0.040)	(0.027)
Explained	-0.015	-0.016*	0.039*	0.019
	(0.014)	(0.008)	(0.022)	(0.013)
Unexplained	-0.016	-0.011	-0.071**	-0.043*
	(0.023)	(0.018)	(0.035)	(0.025)
Explained				
Managerial quality index	-0.008*	-0.005*	-0.003	-0.002
	(0.004)	(0.003)	(0.007)	(0.004)
Management human capital index	-0.004	-0.002	0.000	0.000
	(0.005)	(0.003)	(0.004)	(0.003)
Innovation and skills index	-0.002	-0.001	-0.000	-0.000
	(0.003)	(0.002)	(0.005)	(0.002)
Size	0.000	0.000	0.009	0.005
	(0.005)	(0.003)	(0.006)	(0.003)
Multinational	0.001	0.000	0.003	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Exporter	-0.004	-0.002	-0.002	-0.001
	(0.003)	(0.002)	(0.004)	(0.002)
Government Support	-0.007***	-0.004**	-0.004	-0.004*
	(0.003)	(0.002)	(0.003)	(0.002)
Interaction MNEs	0.004*	-0.001	0.006*	0.001
	(0.002)	(0.001)	(0.003)	(0.001)
Sector	0.005	-0.000	0.030***	0.017**
	(0.004)	(0.003)	(0.011)	(0.008)
Unexplained				
Managerial quality index	-0.045	-0.028	-0.071	-0.024
	(0.034)	(0.026)	(0.058)	(0.042)
Management human capital index	0.054	0.035	-0.040	0.002
	(0.038)	(0.028)	(0.060)	(0.042)
Innovation and skills index	-0.016	-0.016	0.004	0.002
	(0.020)	(0.017)	(0.027)	(0.019)
Size	0.005	-0.014	-0.004	0.045
	(0.030)	(0.024)	(0.042)	(0.036)
Multinational	0.041	-0.002	0.109**	0.026
	(0.033)	(0.028)	(0.045)	(0.033)
Exporter	-0.006	0.009	-0.026	-0.018
	(0.025)	(0.022)	(0.035)	(0.029)
Government Support	-0.015	-0.005	-0.055**	-0.026
	(0.018)	(0.013)	(0.023)	(0.017)
Interaction MNEs	0.011	-0.012	-0.000	-0.032
	(0.026)	(0.021)	(0.038)	(0.029)
Sector	-0.056	-0.049*	-0.057	-0.038
	(0.040)	(0.028)	(0.045)	(0.036)
Observations	11830	11831	7466	7428

Note: This table presents the Oaxaca-Blinder decomposition results. MTF = Male Top Manager and FTM = Female Top Manager. All estimates employ sampling weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Altogether, these results highlight some crucial aspects in which public policies can improve technology adoption by FTM and, in turn, reduce the productivity gap. Much attention has been given to policies tackling the gender digital divide, mainly focusing on increasing women's participation in STEM and high technology sectors, fostering digital literacy, and addressing social norms and stereotypes (Borgonovi et al., 2018). In addition to those, and more directly linked to women in business, our results suggest public policies can have a critical role by incentivizing the adoption of improved managerial practices and offering technology upgrading programs that incorporate gender components to ensure women have equal access and benefit accordingly.

8 Concluding remarks

The role of women in management positions in firm performance has been an important topic for researchers and policy makers. However, the evidence is limited. Using a novel dataset with granular information on technology adoption, this paper sheds some light on this literature by exploring the role of technological sophistication as a potential mediating factor in narrowing productivity differences.

The analysis shows that FTM firms tend to be less productive. Interestingly, we find little to no difference in adopting advanced technologies associated with general business functions at the extensive and intensive margins. However, firms with FTM present lower adoption rates of more sophisticated technologies linked to sector-specific business functions, especially in the Food Processing and Wearing Apparel sectors. Finally, our analysis suggests that technology positively mediates the association between FTM and firm productivity. In particular, the findings indicate that female-managed businesses tend to experience lower productivity returns from technologies when the technology sophistication level is low. However, they begin to catch up quickly as their sophistication level increases at the point where firms intensively use some machines that require human interaction (e.g., a computer with basic software), and the higher returns to technology increase with the digitalization of most business functions. These patterns hold true for both GBF and SBF technologies, suggesting that the intensive use of more sophisticated technologies helps female-managed businesses reduce the productivity gap. Several factors may explain why these returns to technology tend to be larger for female-managed businesses. For example, women are often responsible for juggling multiple roles, and digital technologies might help them make efficient use of time. More research is needed to better understand these mechanisms on the better use of technology.

These results highlight the importance of considering the level of technological sophistication when examining the impact of female top management on firm performance. In addition to spurring firm performance, technology may have an important role in closing the gender gap in productivity, hence opening important avenues for public policy. Upgrading policies coupled with gender-oriented targets could effectively enhance firms' productivity and competitiveness and reduce the gender productivity gap. This could involve targeted initiatives to support accessing and adopting technologies, including efforts to address information asymmetries, skills gaps, and other systemic barriers hindering women's access to financial resources.

However, this study is not without limitations, many of which may indicate fruitful avenues for future research. The availability of longitudinal information on firms' adoption of advanced technologies coupled with changes in top managerial positions could help mitigate possible endogeneity concerns and improve our understanding of this issue. There is likewise ample scope for future research to consider different measures of firm performance, including innovation activities and other productivity measures, as well as different mediating factors.

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Appendix A The Model

We start with a simple model of establishments' production function:

$$Y_i = K_i^{\alpha} L_i^{\beta} I_i^{\gamma} e^{\delta T_i} e^{\zeta FTM_i} e^{\eta X_i} \tag{6}$$

where Y_i is output, K_i is the establishment's capital stock, and L_i and I_i are labor and intermediate inputs. T_i is the technology sophistication score, and X_i is a vector of additional factors, such as the manager's education or experience. Dividing by labor and taking logs allows us to rewrite the equation as follows:

$$log\left(\frac{Y_i}{L_i}\right) = \alpha log\left(\frac{K_i}{L_i}\right) + \gamma log\left(\frac{I_i}{L_i}\right) + (\alpha+\beta+\gamma-1)log(L_i) + \delta T_i + \zeta FTM_i + \eta X_i \tag{7}$$

Appendix B Additional estimates

Table B1: Summary table

	Mean	Median	SD	Min	Max	N
Log(Labor Productivity)	10.03	10.02	2.23	-9.42	26.39	8,751
Number of employees	40.98	10.00	286.74	0.00	20750.00	12,389
Multinational	0.11	0.00	0.31	0.00	1.00	14,585
Exporter	0.13	0.00	0.33	0.00	1.00	14,424
Interaction with MNEs	0.24	0.00	0.42	0.00	1.00	14,585
Government support	0.12	0.00	0.32	0.00	1.00	14,585
Managerial quality index	0.36	0.44	0.24	0.00	1.00	14,583
Non-Family company	0.09	0.00	0.28	0.00	1.00	13,887
Formal incentives	0.68	1.00	0.47	0.00	1.00	14,312
Performance indicators	0.32	0.33	0.30	0.00	1.00	14,282
Management human capital index	0.30	0.29	0.23	0.00	1.00	14,585
Manager's with college	0.61	1.00	0.49	0.00	1.00	14,585
Manager's experience (years)	18.27	15.00	14.60	1.00	60.00	14,585
Experience in large company	0.21	0.00	0.41	0.00	1.00	13,716
Studied abroad	0.12	0.00	0.33	0.00	1.00	13,212
Innovation and skills index	0.18	0.07	0.24	0.00	1.00	13,802
Share of college-educated employees	0.26	0.10	0.32	0.00	1.00	11,841
Share of R&D employees	0.07	0.00	0.17	0.00	1.00	10,238
Innovation	0.20	0.00	0.40	0.00	1.00	11,625

Note: Estimates are weighted by sampling weights

Table B2: Difference in technology use between female and male top managers

	Male		Female		Difference		
	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Business Administration							
Computers with specialized software	0.18	0.37	0.19	0.42	0.01	-0.01	-0.01
Enterprise Resource Planning (ERP)	0.05	0.21	0.06	0.25	0.01	-0.01	-0.01*
Production Planning							
Specialized software for production	0.07	0.26	0.08	0.29	0.01	0.00	0.00
Enterprise Resource Planning (ERP)	0.04	0.19	0.04	0.22	0.00	-0.01*	-0.01*
Supply Chain Management							
Supplier Relation Management (SRM)	0.02	0.14	0.01	0.13	-0.01	-0.01	-0.01
Supplier Relation Management (SRM) integrated	0.01	0.11	0.02	0.13	0.00	-0.00	-0.00
Marketing							
Customer Relationship Management (CRM)	0.03	0.17	0.03	0.19	0.00	-0.00	-0.00
Big data Analytics or Machine learning	0.00	0.07	0.00	0.04	-0.00*	-0.00*	-0.00
Sales Methods							
External digital platforms	0.01	0.08	0.01	0.08	-0.00	-0.00	-0.00
Online sales (e-commerce) using its own website	0.02	0.13	0.02	0.16	0.01	0.00	0.00
Electronic orders integrated to SCM system	0.01	0.10	0.02	0.13	0.00	-0.00	-0.00
Payment Methods							
Online or eletronic payment through a bank wire	0.19	0.38	0.20	0.43	0.02	-0.04**	-0.03*
Online payment through platform	0.02	0.12	0.02	0.14	0.00	0.00	0.00
Virtual or Cryptocurrency	0.00	0.01	0.00	0.00	-0.00	-0.00	-0.00
Quality Control							
Statistical process control	0.05	0.22	0.06	0.24	0.00	0.01	0.01
Automated systems	0.01	0.09	0.02	0.15	0.01	0.01	0.01

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Table B3: Difference in technology adoption between female and male top managers in Agriculture

	Male		Female		Difference		
	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Land Preparation							
Tractors, motor tillers, rotators	0.59	0.71	0.55	0.70	-0.04	-0.02	-0.04
Equipment with digital enabled technologies	0.06	0.34	0.08	0.38	0.02	0.03	0.02
Irrigation							
Drip irrigation	0.28	0.68	0.21	0.60	-0.07	-0.01	-0.02
Automated system controlled by sensors	0.07	0.39	0.06	0.35	-0.01	0.03	0.03
Pest control							
Fully-automated Variable Rate Application (VRA)	0.16	0.56	0.15	0.52	-0.02	0.03	0.02
Advanced Precision Agriculture	0.03	0.25	0.00	0.05	-0.03***	-0.03**	-0.03**
Harvesting							
Mechanized process with machines or tractors	0.19	0.61	0.09	0.43	-0.10*	-0.04	-0.04
Automated process with machines or tractors	0.08	0.43	0.06	0.36	-0.03	0.00	0.01
Storage							
High-end central storage facilities	0.13	0.45	0.12	0.44	-0.01	0.01	0.00
Continuous temperature monitoring device	0.08	0.37	0.02	0.20	-0.06***	-0.05**	-0.07**
Packing							
Automated packing	0.14	0.52	0.13	0.48	-0.01	0.02	0.02
Modified atmosphere packing	0.08	0.41	0.06	0.34	-0.02	-0.01	-0.01

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Difference in technology adoption between female and male top managers in Food Processing

	Male		Female		Difference		
	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Input Testing							
Non-computer-controlled testing kits	0.27	0.74	0.20	0.56	-0.07*	-0.09**	-0.06
Computer testing	0.11	0.52	0.03	0.26	-0.07***	-0.09***	-0.05**
Mixing/blending/cooking							
Power equipment requiring human interaction	0.54	0.82	0.51	0.70	-0.03	-0.03	-0.01
Power equipment controlled by computers or robotics	0.09	0.48	0.04	0.26	-0.06***	-0.04**	-0.03
Anti-bacterial processes							
Thermal Processing Technologies	0.44	0.82	0.34	0.69	-0.09*	-0.12**	-0.07
Advanced methods (e.g, High-pressure processing)	0.07	0.42	0.04	0.29	-0.03	-0.03	-0.00
Packaging							
Power equipment requiring routine human interaction	0.41	0.80	0.22	0.60	-0.19***	-0.22***	-0.18***
Power equipment controlled by computers or robotics	0.06	0.40	0.03	0.23	-0.04**	-0.05**	-0.03*
Food storage							
Some climate control in secured building	0.43	0.80	0.39	0.69	-0.04	-0.07	-0.05
Fully automated climate and security-controlled	0.22	0.67	0.12	0.45	-0.10**	-0.12**	-0.08

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Difference in technology adoption between female and male top managers in Wearing Apparel

	Male		Female		Difference		
	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Design							
Computer-Aided Design (CAD) or 3D design	0.08	0.36	0.06	0.54	-0.02	-0.14***	-0.12***
Cutting							
Automatic or Computerized cutting machine	0.05	0.30	0.05	0.47	0.00	-0.05*	-0.04
Automatic/Computerized cutting machine (Laser)	0.01	0.12	0.01	0.24	0.01	-0.01	-0.01
Sewing							
Automated sewing machines	0.16	0.52	0.25	0.89	0.10	0.06	0.06
3D Knitting	0.01	0.12	0.00	0.07	-0.01	-0.01*	-0.00
Ironing							
Form finishing machine	0.08	0.37	0.06	0.46	-0.02	-0.05	-0.05
High tech pressing machine	0.03	0.23	0.04	0.37	0.01	-0.02	-0.01

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table B6: Difference in technology adoption between female and male top managers in Retail

	Male		Female		Difference		
	Mean	SD	Mean	SD	Uncond.	Cond.	Cond.
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Customer service							
Social Media	0.30	0.32	0.39	0.37	0.10*	0.04	0.03
Online requests	0.17	0.26	0.17	0.29	-0.00	-0.04	-0.05
Chatbots	0.04	0.13	0.04	0.14	-0.00	-0.01	-0.01
Pricing							
Dynamic pricing systems	0.09	0.20	0.07	0.19	-0.02	-0.03	-0.03
Personalized pricing driven by predictive analytics	0.04	0.13	0.02	0.11	-0.01	-0.02	-0.02
Merchandising							
Retail Merchandising Systems or Digital Merchandising	0.14	0.24	0.17	0.28	0.02	-0.00	-0.01
Product trend analytics	0.04	0.14	0.03	0.13	-0.01	-0.02	-0.02
Inventory							
Automated inventory control (CAO)	0.03	0.13	0.06	0.18	0.03	0.02	0.02
Automated Storage and Retrieval systems (AS/RS)	0.04	0.14	0.03	0.12	-0.01	-0.02	-0.03
Advertisement							
Social Media	0.45	0.35	0.48	0.39	0.02	0.01	-0.01
Search Engine Marketing	0.14	0.24	0.08	0.22	-0.05	-0.06	-0.07*
Big data Analytics or Artificial Intelligence	0.03	0.12	0.02	0.11	-0.01	-0.02	-0.02

Note: Table shows averages for baseline using sampling weights. The fifth column presents the unconditional difference, the sixth column presents the coefficients of linear regressions of each variable on female top management controlling for country fixed effects, and the seventh column adds sector and size group dummies. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table B7: OLS estimates of the adoption of GBF technologies

	GBF EXT			GBF INT		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
Female Top Manager	-0.0251			-0.0274		
	(0.0236)			(0.0180)		
Managerial quality index	0.467***	0.495***	0.377***	0.307***	0.323***	0.254***
	(0.0456)	(0.0539)	(0.0989)	(0.0342)	(0.0402)	(0.0763)
Management human capital index	0.587***	0.544***	0.720***	0.337***	0.305***	0.467***
	(0.0522)	(0.0597)	(0.137)	(0.0381)	(0.0436)	(0.0984)
Innovation and skills index	0.365***	0.382***	0.266**	0.242***	0.263***	0.144
	(0.0508)	(0.0590)	(0.122)	(0.0377)	(0.0425)	(0.102)
Multinational	-0.0373	-0.0213	-0.0910	-0.0102	-0.0117	0.0132
	(0.0330)	(0.0372)	(0.0909)	(0.0253)	(0.0280)	(0.0811)
Exporter	0.218***	0.217***	0.242***	0.133***	0.138***	0.109*
	(0.0295)	(0.0345)	(0.0645)	(0.0211)	(0.0235)	(0.0620)
Interaction with MNEs	0.149***	0.143***	0.180***	0.0755***	0.0723***	0.0934*
	(0.0252)	(0.0287)	(0.0656)	(0.0173)	(0.0191)	(0.0502)
Government support	0.173***	0.174***	0.155**	-0.0173	-0.0229	-0.00929
	(0.0302)	(0.0358)	(0.0632)	(0.0256)	(0.0303)	(0.0519)
Financial constraints	0.125***	0.125***	0.124**	-0.0196	-0.0231	-0.00222
	(0.0217)	(0.0242)	(0.0580)	(0.0141)	(0.0152)	(0.0413)
Formality	-0.101***	-0.137***	0.104*	-0.0585***	-0.0600***	-0.0344
	(0.0215)	(0.0243)	(0.0566)	(0.0122)	(0.0141)	(0.0334)
Medium	0.266***	0.277***	0.253***	0.167***	0.165***	0.193***
	(0.0222)	(0.0259)	(0.0515)	(0.0158)	(0.0179)	(0.0411)
Large	0.506***	0.515***	0.504***	0.332***	0.339***	0.306***
	(0.0377)	(0.0434)	(0.0881)	(0.0281)	(0.0322)	(0.0743)
Constant	-0.860***	-0.831***	-1.062***	-0.357***	-0.345***	-0.451***
	(0.0334)	(0.0372)	(0.0890)	(0.0218)	(0.0248)	(0.0531)
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13087	10137	2950	13090	10140	2950
R-squared	0.316	0.323	0.305	0.227	0.233	0.207

Note: This table presents linear regressions of different technology indexes for GBFs on firms' characteristics, controlling for country, sector, formality, and size. All estimates are weighted by sampling and country weights weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B8: OLS estimates of the adoption of SBF technologies

	GBF EXT			GBF INT		
	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
Female Top Manager	-0.0522			-0.0509*		
	(0.0378)			(0.0266)		
Managerial quality index	0.511***	0.546***	0.395**	0.345***	0.370***	0.273**
	(0.0721)	(0.0819)	(0.181)	(0.0573)	(0.0669)	(0.138)
Management human capital index	0.442***	0.436***	0.356	0.251***	0.219***	0.338**
	(0.0863)	(0.0973)	(0.231)	(0.0671)	(0.0800)	(0.156)
Innovation and skills index	0.418***	0.419***	0.410**	0.196***	0.210**	0.139
	(0.0852)	(0.101)	(0.186)	(0.0667)	(0.0816)	(0.124)
Multinational	-0.122**	-0.0735	-0.334***	-0.0949**	-0.0774*	-0.149
	(0.0494)	(0.0570)	(0.122)	(0.0381)	(0.0448)	(0.0909)
Exporter	0.193***	0.185***	0.250**	0.0936**	0.0877**	0.115
	(0.0442)	(0.0510)	(0.110)	(0.0372)	(0.0433)	(0.0888)
Interaction with MNEs	0.114***	0.0794*	0.271***	0.0855***	0.0688*	0.175***
	(0.0383)	(0.0450)	(0.0806)	(0.0293)	(0.0354)	(0.0602)
Government support	0.187***	0.174***	0.221**	0.0809**	0.0576	0.141*
	(0.0440)	(0.0513)	(0.102)	(0.0382)	(0.0475)	(0.0755)
Financial constraints	0.116***	0.120***	0.103	0.00240	-0.00611	0.0383
	(0.0330)	(0.0365)	(0.101)	(0.0239)	(0.0276)	(0.0595)
Formality	-0.0396	-0.0581	0.0420	0.0182	0.00600	0.100*
	(0.0326)	(0.0377)	(0.0898)	(0.0228)	(0.0270)	(0.0513)
Medium	0.254***	0.279***	0.174**	0.120***	0.134***	0.0928
	(0.0347)	(0.0401)	(0.0780)	(0.0264)	(0.0311)	(0.0621)
Large	0.564***	0.554***	0.611***	0.313***	0.344***	0.211**
	(0.0532)	(0.0631)	(0.115)	(0.0483)	(0.0565)	(0.0983)
Constant	-0.262***	-0.251***	-0.340***	0.00576	0.0251	-0.143
	(0.0442)	(0.0495)	(0.123)	(0.0341)	(0.0383)	(0.0981)
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8765	6650	2115	8724	6619	2105
R-squared	0.298	0.308	0.280	0.213	0.221	0.215

Note: This table presents linear regressions of different technology indexes for SBFs on firms' characteristics, controlling for country, sector, formality, and size. All estimates are weighted by sampling and country weights weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix C Controlling for sector-by-region fixed effects

Table C1: OLS estimates of productivity and technology gaps

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)	(5) Ln(VAPW)	(6) Ln(VAPW)	(7) Ln(VAPW)
Female Top Manager	-0.485*** (0.0880)	-0.426*** (0.0907)	-0.283*** (0.0999)	-0.279*** (0.100)	-0.273*** (0.100)	-0.293** (0.137)	-0.299** (0.138)
Log(Capital per worker)			0.276*** (0.0294)	0.256*** (0.0283)	0.265*** (0.0291)	0.257*** (0.0434)	0.259*** (0.0439)
Log(Employment)			-0.0401 (0.0420)	-0.112*** (0.0432)	-0.0890** (0.0443)	-0.0703 (0.0595)	-0.0445 (0.0578)
GBFs - Extensive margin				0.282*** (0.0616)			
GBFs - Intensive margin					0.373*** (0.0861)		
SBFs - Extensive margin						0.151** (0.0693)	
SBFs - Intensive margin							0.145 (0.101)
Formality	2.215*** (0.156)	1.989*** (0.177)	1.739*** (0.190)	1.653*** (0.189)	1.622*** (0.192)	1.770*** (0.237)	1.790*** (0.238)
Management human capital index		0.672*** (0.193)	0.570** (0.226)	0.317 (0.230)	0.392* (0.226)	0.177 (0.342)	0.211 (0.346)
Constant	7.183*** (0.248)	7.765*** (0.216)	5.294*** (0.372)	5.801*** (0.364)	5.611*** (0.368)	5.530*** (0.502)	5.368*** (0.501)
Sector X Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8579	8579	6717	6717	6717	4370	4362
R-squared	0.342	0.386	0.535	0.542	0.541	0.541	0.538

Note: This table presents the OLS regression results. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. Estimates were performed using sample weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C2: Two-Stages Least Squares

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)	(5) Ln(VAPW)	(6) Ln(VAPW)	(7) Ln(VAPW)
Female Top Manager	-0.620***	-0.612***	-0.451***	-0.455***	-0.432***	-0.537***	-0.541***
	(0.121)	(0.121)	(0.119)	(0.119)	(0.121)	(0.150)	(0.151)
Log(Capital per worker)			0.277***	0.257***	0.266***	0.253***	0.255***
			(0.0277)	(0.0267)	(0.0275)	(0.0396)	(0.0399)
Log(Employment)			-0.0386	-0.111***	-0.0870**	-0.0657	-0.0403
			(0.0392)	(0.0404)	(0.0413)	(0.0541)	(0.0524)
GBFs - Extensive margin				0.280***			
				(0.0565)			
GBFs - Intensive margin					0.368***		
					(0.0792)		
SBFs - Extensive margin						0.148**	
						(0.0630)	
SBFs - Intensive margin							0.141
							(0.0914)
Formality	2.213***	2.015***	1.764***	1.680***	1.653***	1.797***	1.819***
	(0.167)	(0.175)	(0.181)	(0.180)	(0.183)	(0.220)	(0.221)
Management human capital index		0.613***	0.508**	0.259	0.335	0.139	0.174
		(0.190)	(0.215)	(0.217)	(0.213)	(0.312)	(0.315)
Constant	7.716***	7.754***	5.272***	5.779***	5.579***	5.540***	5.379***
	(0.211)	(0.211)	(0.349)	(0.339)	(0.345)	(0.457)	(0.457)
Sector X Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8423	8423	6627	6627	6627	4317	4309
R^2	0.384	0.386	0.537	0.543	0.542	0.540	0.536
F	316.1	319.0	236.2	236.6	237.2	148.4	148.2
J	0.000201	0.00013318	0.643	0.485	0.942	0.219	0.355

Note: This table presents the 2SLS regression results. Exclusion restrictions are the regional share of FTM and female ownership. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. Estimates were performed using sample weights. Robust standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C3: OLS estimates of productivity and technology gaps

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)
Female Top Manager	-0.277***	-0.263***	-0.294**	-0.294**
	(0.100)	(0.0992)	(0.137)	(0.135)
GBFs - Extensive margin	0.267***			
	(0.0674)			
FTM*GBF EXT	0.0932			
	(0.137)			
GBFs - Intensive margin		0.289***		
		(0.0955)		
FTM*GBF INT		0.399***		
		(0.148)		
SBFs - Extensive margin			0.138*	
			(0.0739)	
FTM*SBF EXT			0.0672	
			(0.157)	
SBFs - Intensive margin				0.0934
				(0.102)
FTM*SBF INT				0.299
				(0.226)
Sector	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Sector X Region	Yes	Yes	Yes	Yes
Observations	6717	6717	4370	4362
R-squared	0.542	0.542	0.542	0.539

Note: All estimates control for capital stock, employment, sector, country, and additional controls, including formality and the management human capita index. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. Estimates were performed using sample weights. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C4: 2SLS estimates for the interaction between productivity and technologies

	(1) Ln(VAPW)	(2) Ln(VAPW)	(3) Ln(VAPW)	(4) Ln(VAPW)
Female Top Manager	-0.353***	-0.334***	-0.479***	-0.472***
	(0.128)	(0.118)	(0.148)	(0.145)
GBF EXT	0.165**			
	(0.0840)			
FTM*GBF EXT	0.689*			
	(0.377)			
GBF INT		0.191		
		(0.118)		
FTM*GBF INT		0.849**		
		(0.364)		
SBF EXT			0.0427	
			(0.0932)	
FTM*SBF EXT			0.584	
			(0.394)	
SBF INT				0.00373
				(0.114)
FTM*SBF INT				0.827*
				(0.478)
Controls	Yes	Yes	Yes	Yes
Sector X Region	Yes	Yes	Yes	Yes
Observations	6627	6627	4317	4309
R^2	0.535	0.542	0.533	0.535
Shea's R-squared	0.373	0.397	0.398	0.408
Shea's R-squared	0.0271	0.0964	-0.0338	0.0289
J	0.678	0.354	0.243	0.0146

Note: This table presents the 2SLS regression results. Exclusion restrictions are the regional share of FTM and female ownership and the interaction of each variable with the technology indexes. All estimates control for capital stock, employment, sector, region, sector X region, and additional controls, including formality and the management human capita index. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates were performed using sample weights. Robust standard errors are in parentheses.

Appendix D Propensity Score Matching

This section develops additional robustness checks by applying propensity score matching (PSM) to account for differences in firms' observable characteristics. In particular, PSM estimates the probability of receiving a given treatment (in our case, having a FTM), conditional on the firms' characteristics. The propensity score can be described by Equation 8:

$$p(X) = Pr\left\{D = 1|X\right\} = E\left\{1|X\right\} \tag{8}$$

where $D = \{0, 1\}$ is the treatment indicator, and X is the same vector as in Equation 1. Following the propensity score estimates, we apply different matching algorithms, including radius, kernel, and nearest neighbor matching, and estimate the average treatment effect on the treated (ATT).

Table D1 presents similar results using alternative methods. In Table D1, each column indicates a different matching algorithm, suggesting statistically significant coefficients ranging from -0.18 to -0.24. Although smaller in magnitude, the coefficients confirm that firms with FTM are less productive. Moreover, the PSM estimates indicate a lack of differences in technology adoption.

Table D1: ATT - Propensity Score Matching

	Productivity		
VARIABLES	Nearest	Kernel	Radius
Productivity			
ATT	-.2459944	-.1832166	-.1540374
SE	.060547	.0631779	.0619417
GBF EXT			
ATT	-.0054658	-.0274711	-.0296056
SE	.0263593	.0278504	.0273161
GBF INT			
ATT	.0004158	-.0040698	.0066825
SE	.0212217	.0217357	.0213781
SBF EXT			
ATT	-.0418604	-.0276298	-.0200757
SE	.033058	.0353978	.0345881
SBF INT			
ATT	-.0206278	-.0342562	-.0193885
SE	.026719	.0279253	.0273529

Note: Table presents the results of the average treatment effect on the treated (ATT) for different dependent variables and using different matching algorithms. The first column uses the nearest neighbor matching algorithm without replacement and with a 0.1 caliper. The second column employs a kernel algorithm, while the third uses a radius algorithm without replacement and with a 0.1 caliper. All estimates control for sector, region, and additional controls, including formality, the logarithm of capital per worker, the logarithm of employment, and the management human capital index. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D2: OLS estimates of the interaction between technology and FTM by country

	GBF Ext	GBF Int	SBF Ext	SBF Int
Brazil				
Beta	.3834813	.4896337	.7970027**	.6769903*
SE	.4056493	.3626696	.3478688	.3900935
Ethiopia				
Beta	1.002126**	.9581375	.7278214***	.9042379***
SE	.4311515	.6316299	.2811608	.3711437
Georgia				
Beta	.465247	.3004923	.1609648	.0190962
SE	.44331	.5264713	.4808747	.4411912
Ghana				
Beta	.0784284	.1896712	-.0302532	-.3595751
SE	.2297451	.4119652	.324572	.5339248
Kenya				
Beta	-.0723301	.4277657	-.011962	.7173565***
SE	.2479054	.3571949	.3026101	.3408149
Korea, Rep.				
Beta	-.5074001	-.4332795	.1561223	-.118689
SE	.27379	.278991	.2645521	.2739005
Senegal				
Beta	.5373342*	.8432004*	.4715511	.6147281
SE	.2985337	.5103802	.3715586	.5810499
Viet Nam				
Beta	.0747039	.1959651	-.1876918	-.6162573
SE	.2721648	.3884955	.2280807	.3568495

Note: Table presents the coefficients of the interaction between FTM and each technology index. All estimates control for sector and additional controls, including formality, the logarithm of capital per worker, the logarithm of employment, and the management human capital index. FTM = Female Top Manager, GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.