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Access to finance: The role of production level technology

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ABSTRACT

The integration of robots and advanced technology in firm-level production processes represents a transformative shift in modern industrial practices. However, there is a lack of cumulative knowledge about the advancement of technology in the production processes affects mitigating the gender gap. Through the lens of financial accessibility, the study investigates how technological advancements influence firms' capacity to secure external financing and get large loans. Using the 2020 WorldBank Enterprises Survey data and a probit model for the analysis, our results suggest that industry robots and a high level of technology in production have the potential to reduce the gender gap in loan approvals. The findings of this have implications for decision-makers and policymakers, seeking to navigate the evolving landscape of technology-driven production and finance to enhance productivity and inclusivity.

1. Introduction

Adopting emerging technologies allows firms to gain a competitive edge (Beck et al., 2005). The use of robots and a high level of technology in the production process is a key driver for boosting productivity and efficiency and may result in generating better quality jobs (Albinowski & Lewandowski, 2024), resilience to shock (UN Trade and Development, 2020) and firm value (Li et al., 2024). Investment in industrial robots and high levels of technology has a dual effect on firms' financial dynamics. First, in line with Li et al. (2024), we argue that increasing capital investment in the production process reduces the agency problem. Industrial robots and high levels of technology reduce the amount of cash they have on hand which prevents corporate managers undertaking market monitoring. This leads to mitigating agency costs by aligning management and shareholder interests (Li et al., 2024). Second, a lack of corporate cash holdings may result in firms resorting to borrowing. High firm value (Li et al., 2024), quality of products (Dixon et al., 2021), productivity (Faber, 2020), and the use of technology in the production process should increase the number of credit applications made, which leads to enhancing the approval of credit applications.

Given the importance of the manufacturing sector to a country's economy, it is important to identify the degree of access to finance within the industry. Prior research indicates that technology increases the productivity of manufacturing firms (see Hall, Lotti & Mairesse, 2013). In addition, Kromann et al., (2020) show that automation of a production process, via robots, increases total factor productivity. Technology therefore has an obvious impact on productivity either directly or indirectly (through R&D or other innovations).

Prior studies have explored the impact of technology adaptation and access to finance. Many of these studies focus on the impact

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financial technologies have on technology adoption (Abbasi, Alam, Brohi, Brohi & Nasim, 2021; Huang, 2022). Over the past decades, factory floors have been revolutionized by advancements in robotics and high-level technologies, significantly altering the landscape of manufacturing (PwC, 2018). Linking technology adoption, in general, to the propensity to obtain finance is a challenging task, especially with the dearth of literature touching on this subject. On one hand, the adoption of new technologies can be associated with perceptions of risk and uncertainty (Pavlou & Gefen, 2004), however, this may only affect firms during the adoption period. High levels of technology and / or robot adoption have business related benefits. Production efficiency has been found to increase in the presence of virtual reality (Xiong, Lam & Karimi, 2024), artificial intelligence, machine learning and blockchain (Jha & Sachan, 2023; Awogbemi & Kallon, 2023), and robots (Xie et al., 2022; Liu et al., 2019), amongst others. This efficiency would, or should, be recognized by banks as an input to future growth which in turn would be expected to increase the probability that firms using these technologies would be more likely to obtain finance. As suggested, there is a dearth of literature linking high technology adoption and access or receiving finance, hence, it is important to empirically examine how robots and high levels of technology impact firm financing.

H1. Advancement in technology by manufacturing firms has a positive effect on access to credit facilities.

Gender disparities in access to finance frequently stem from institutional and market failures on both sides of financial markets, alongside specific attributes of women-owned firms such as size, sector, and age. Recent literature highlights that access to finance can be difficult for women (see, for instance, the meta-analysis by Malmström et al. (2024)). Further, the literature indicates that women require more collateral (Bellucci et al., 2010), the loans are generally smaller (Coleman & Robb, 2009) and the rates paid on loans are usually higher (Mascia & Rossi, 2017), comparatively to men. Stiglitz and Weiss (1981) highlight that information asymmetries give rise to adverse selection however the question of whether technology in the form of robots alleviates information asymmetries is unanswered. In related works, Hogan and Hutson (2005) show that for 'new technology-based firms' information asymmetry exists, though venture capitalists overcome information asymmetries. There is a lack of cumulative knowledge about the advancement of technology in the production processes effect on mitigating the gender gap. Hence, this study empirically examines how high levels of technology mitigate the gender gap in access financing. Effort in this direction helps to formulate policies and programs aimed at bridging this gap.

H2. Advancement in technology has a mitigating effect on the gender gap in access to credit facilities.

In this study, we utilize firm-level data of unlisted firms from 10 European countries that have high technology and robot density in the manufacturing sector. Our results demonstrate that technology adoption in the production process has a positive impact on credit approval and large loan size. Further, we find that the technology adaptation reduces the gender gap in credit approval and loan size.

This study contributes to knowledge regarding the nuanced relationship between firm-level technology adaptations and access to finance. As one of the first studies that empirically examines the technology adoption in the production process, we extend firm-level technology and its impact on access to credit. A strand of literature has investigated the impact of technology on firms from a variety of perspectives, such as industrial robot adoption on firm value, production, total factor productivity, export, green innovation, and energy performance. Our study contributes to understanding the effects of the use of industrial robots and higher-level technology adoption in manufacturing firms from a credit access perspective. The research in this area is scant and has a relatively micro view. Our research also adds empirical evidence to the existing body of literature on the gender gap for credit accessibility high technology and robot density manufacturing firms. Further, by employing a Heckman probit model this study addresses a common methodological flaw in credit accessibility studies, namely, selection bias. In particular, in our study loan characteristics are solely observable for approved loans, posing a selection bias challenge. Although, prior finance studies acknowledge this issue, only a few studies have successfully controlled for it due to the difficulty in finding suitable instruments. The findings of this study will inform firm owners, finance organizations, researchers, and policy-makers regarding the dynamic interplay between technological adaptations and access to finance.

The remainder of the paper is as follows. The methods employed are detailed in Section 2. In Section 3 we present the data, empirical results, and a discussion. Section 4 concludes.

2. Data and methodology

We collect unlisted firm data from 10 European countries that have high robot density in the manufacturing process. The data was collected from the 2020 WorldBank Enterprises Survey which provides firm-level technological data, credit access data, and firm and ownership characteristics, such as firm age, firm size, firm age, export status, R&D expenditure, firm legal status, and female ownership. The survey uses stratified random sampling to ensure representation across different firm sizes, sectors, and regions within an economy. Data was collected through face-to-face interviews with business owners and top managers. A number of recent studies use the World Bank Enterprise Survey data to study firm-level credit access (See Deng & Qian, 2024; Wellalage et al., 2022). Like most surveys, the Enterprise Surveys may encounter some level of nonresponse. To ensure transparency, nonresponses statistics are included in the Implementation Report accompanying each dataset.[1,2] To avoid potential biases the Enterprise Survey involves careful survey design, clear and neutral question phrasing, and ensuring a representative sample. A number of respondent firms per country and

[1] Please see below link Enterprise Surveys Sampling Methodology, 2022 for more details (https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/methodology/Sampling_Note-Consolidated-2-16-22.pdf)

country-level macroeconomic details are reported in Appendix 1.

Our study employed a probit model with sample selection, which assumes that an underlying relationship exists between credit access and high-level technology adaptation in the production process.

Credit Apply - This variable focuses on possible differences between credit applications made by firms that use technology in the production process or not.

$$Probit\ (Credit\_Apply_{ic} = 1) = \propto_c + (\alpha + \beta Technology_{ic} + \gamma X_{ic} + \varepsilon_{ic}) \tag{1}$$

$$Probit\ (Loan\_Need_{ic} = 1) = \propto_c + (\alpha + \beta Technology_{ic} + \gamma X_{ic} + \partial_1 SalesDecline_{ic} + + \varepsilon_{ic}) \tag{2}$$

Eq. 1 is the main equation of the credit application, and Eq. 2 is the sample selection equation. Eq. 1, $Credit\_Apply_{ic}$ takes value 1 if firms apply for a loan, zero otherwise. *Technology* takes value 1 if the firm adopted technology in the production process, zero otherwise. However, in the sample, a firm *Credit_Apply* is only observable if the firm needs credit. This raises the issue of selection bias which Eq. 2 seeks to address. To address selection bias, we use the *Sales_Decline* variable in the selection equation, which affects the credit need but does not affect the decision to apply for credit (Heckman, 1977). In simpler terms, the sales decline variable helps to identify firms that need credit due to declining sales (relevance), but this need does not necessarily mean they will apply for credit (exogeneity). A sales decline is a relevant indicator because it directly affects a firm's financial health and, consequently, its need for credit (Wellalage et al., 2022). Also, the sales decline instrument is not correlated with the error term in the outcome equation (the decision to apply for credit). This instrument is valid because the final decision for firms to apply for a loan is influenced by other factors. For instance, firms might secure funding from internal sources before turning to formal ones (Pham & Talavera, 2018).

Loan Approval - This variable focuses on possible differences between the loan approval rates of firms that adopted high technology in the production process and those not by formal financial institutions.

$$Probit\ (Loan = 1) = \propto_c + (\propto_i + \beta Technology_{ic} + \gamma X_{ic} + \varepsilon_{it}) \tag{3}$$

$$\begin{aligned} &Probit\ (Credit\_Apply_{ic} = 1) \\ &= + (\propto_i + \beta Technology_{ic} + \mu Y_{ic} + \partial_1 Supplier\_Credit_{ic} + \varepsilon_{it}) \end{aligned} \tag{4}$$

Our *Supplier_Credit* variable takes the value of one if firms have a loan from a supplier of credit. Similar instrument variables are used by Pham and Talavera (2018).[2] We find instruments that affect the probability of applying for a bank loan without influencing the approval decision. Supplier credit serves as a supplement to bridge the gap left by the formal sector and is often preferred. Hence, we can argue that if a firm has supplier credit, it is less likely to apply for loans from formal sources. This instrument is valid because banks cannot observe supplier credit applications when making decisions on bank loan applications.

Loan term - This variable focuses on possible differences in the loan terms issued by banks between firms that adopted technology in the production process or not. We consider two credit terms: (i) Loan to collateral ratio and (ii) Loan size.

$$Probit\ (Collateral_{ic} = 1) = \propto_c + (\propto_i + \beta Technology_{ic} + \mu Y_{ic} \varepsilon_{it}) \tag{5a}$$

$$Probit\ (DLoansize_{ic} = 1) = \propto_c + (\propto_i + \beta Technology_{ic} + \mu Y_{ic} + \varepsilon_{it}) \tag{5b}$$

$$\begin{aligned} &Probit\ (Loan_{ic} = 1) = \\ &\propto_c + (\propto_i + \beta Technology_{ic} + \mu Y_{ic} + \partial_2 Mgr\_Time_{ic} + \partial_3 Crime_{ic}\ \varepsilon_{it}) \end{aligned} \tag{6}$$

We use senior manager time spent on dealing with regulations (*Mgr_Time*) and crime (*Crime*) as an instrument. We assume that if a senior manager spent more time dealing with regulations, the likelihood of firms receiving loans without collateral would be higher. The validity of the Mgr_Time and Crime variables as an instrument in the Heckman selection model satisfies the relevance and endogeneity criteria, i.e., the instrument(s) must be correlated with the endogenous explanatory variable (in this case, Loan approval). Also, the instrument(s) must not be correlated with the error term in the outcome equation (loan-to-collateral ratio and loan size). Losses as a result of crime may cause a temporary reduction in the available liquidity of firms, and that leads to the approval of small loans. In their study, Qi and Ongena (2019) use *Crime exposure* as an instrument variable in their first stage Heckman selection model. However, similar to prior studies we acknowledge that valid instrumental variables are challenging because finding instruments that are both relevant and exogenous is difficult in cross-sectional datasets.

3. Results

Table 1 reports the descriptive statistics of the study sample. Our main explanatory variable is *Technology*. *Technology* takes the value of one if the firm uses computer numerically controlled machine (CNC), robots, additive manufacturing including rapid prototyping and 3D printers or other advanced manufacturing processes (e.g. as laser, plasma sputtering, high-speed machine, E-beam, micromachining) in their production line, otherwise, the variable *Technology* takes the value zero.

Table 2 shows that firms with high levels of technology in their production process are less likely to apply for bank loans compared

[2] In their study, the informal credit variable takes the value of one if firms apply for an informal loan, and zero otherwise (Pham & Talavera, 2018). In contrast, our study considers the current informal loan availability for firms.

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev	Min	Max
Apply_credit	8336	.1089	.1362	0	1
Loan	5224	.5392	.4984	0	1
Large Loan	5711	.5596	.4964	0	1
Collateral	4282	.5140	.4998	0	1
Technology	3825	.0922	.1435	0	1
CNC	3825	.0214	.1448	0	1
Robot	3825	.0329	.1785	0	1
Additive manufacturing	3825	.0324	.1771	0	1
Advanced processes	3825	.0055	.0739	0	1
Lnsales	8040	15.59	1.96	9.21	25.25
Export%	8362	20.86	31.32	0	100
R&D	8339	0.35	0.48	0	1
Firm_Age	8307	37.48	31.06	2	222
Female	8081	0.40	0.49	0	1
Sole_Prop	8362	0.06	0.06	0	1

Notes: All variables are boolean except for Lnsales, Export%, and Firm_Age. Apply_credit takes the value one if a firm has applied for credit in the past X periods. Loan takes the value one if a firm has successfully obtained a loan in the past X periods. Large Loan takes the value one if a firm has successfully obtained a loan of greater than Y size in the past X periods. Collateral takes the value one if a firm requires collateral as part of its successful loan application. Technology takes the value of one if a firm is technologically advanced based on World Bank classifications. CNC takes the value one if a firm uses computer numerically controlled machines in their production process. Robot takes the value one if a firm uses robots in their production process. Additive manufacturing takes the value one if a firm uses additive manufacturing. Advanced processes take the value one if a firm uses advanced processes. Lnsales is the lateral log of a firm's sales. Export% is the percentage of sales that were directly and indirectly exported in the last completed fiscal year. R&D takes the value one if the firm allocated funding for R&D expenses in the last fiscal year. Firm age is the age of the firm in years. Female takes the value one if the owner of the firm is female. Sole_Prop takes the value one if the firm is structured as a sole proprietorship.

to their lower technology counterparts. According to the marginal effects results, firms using high levels of technology in their production process show a 7% lower probability of applying for a bank loan. This infers a demand-side problem for firms with high technology in their production process. Implementation of robots and a high level of technology in the firm production process requires substantial upfront costs which leads to strain on a firm's liquidity in the short-term making it appear riskier to lenders. This may be the main reason that firms with high levels of technology are reluctant to apply for external finance.

The Credit Approval column(s) indicate that firms with high levels of technology in their production process are more likely to get credit approval from banks. Firms that use a high level of technology in their production process have approximately a 0.8% higher probability of credit approval compared to their non-technical counterparts. This accepts H_1. This may be because robots and advanced technologies in the production process act as a favourable indicator of creditworthiness in the lending process due to the following reasons: first, robots and advanced technologies increase operational efficiency by automating repetitive tasks, and production speed. This efficiency translates into higher profitability and cash flow, which are favourable indicators of creditworthiness. Second, adaptation to a high level of technology will boost productivity levels. This higher productivity level increases revenues and improves financial performance, which are key factors considered by lenders when assessing creditworthiness. Third, technology-driven automation can help firms reduce production costs by minimizing labor expenses (Faber, 2020). Cost-effective operations improve the firm's financial health and repayment capacity, making them more attractive to lenders.

Robots and a high level of technology in the firm production process do not affect the collateral requirement of bank loans. However, a high level of technology in the production process positively affects loan size. Our results indicate that firms that adopt robots and high tech in their production process have a 2 % higher probability of having large loans compared to their non-technical counterparts. This may be when firms use high tech in their production process, they may increase their production and firm value, which increases a firm's borrowing capacity. On the other hand, due to the large capital requirements in adopting robots and increasing technology, firms may request large loans.

Table 3 credit Approved column indicates that the interaction term on *Technology* X Female_Own is positive and statistically significant for loan approvals. Intra-group analysis shows us, that female-owned firms with technology leads to 0.54 % (0.21 + (0.33)) more credit approval than female-owned firms without technology. The economic significance of this is substantial, especially when it comes to policy and intervention design. Similarly, the large loan column indicates that *Technology* X Female_Own is positive and statistically significant for large loans. Intra-group analysis shows us, that female-owned firms with technology lead to 12.63 % (3.22 + (9.41)) more large loans than female-owned firms without technology. This result leads to accepting H2. Technology's role in the production process in reducing gender disparity in access to finance is a clear example of how small changes in access and empowerment can lead to significant economic and social improvements.

Overall, our finding indicates that a high level of technology in the production process eases the "gender discrimination" in the credit market for women-owned firms.

3.1. Robustness tests

In this analysis, we split the main explanatory variable into three groups. i.e. computer numerically controlled machines (CNC),

Table 2
Heckprobit results of credit application, credit approval, and loan characteristics.

	Credit apply		Credit approval		Collateral		Large loan	
	Probit	Marginal	Probit	Marginal	Probit	Marginal	Probit	Marginal
Technology	-1848***	-.0669***	.2580***	.0078**	.0071	.0023	.0641*	.0197*
	(.0369)	(.0136)	(.0837)	(.0027)	(.0215)	(.0069)	(.0486)	(.0139)
Lnsales	.0420***	.0152***	.0823*	.0025*	-.0103	-.0033	-.0037	-.0011
	(.0118)	(.0043)	(.0597)	(.0019)	(.0104)	(.0032)	(.0209)	(.0064)
Export%	.0002	.0001	.0012	.0003	-.0004	-.0001	-.0003	-.0000
	(.0002)	(.0001)	(.0010)	(.0003)	(.0009)	(.0003)	(.0004)	(.0001)
R&D	.0086	.0031	.3896***	.0118***	.1167***	.0379***	.2255***	.0693***
	(.0107)	(.0038)	(.1255)	(.0030)	(.0318)	(.0113)	(.0639)	(.0198)
Firm age	-.0001	-.0000	-.0032	-.0013	.0000	8.64e-06	-.0004	-.0001
	(.0001)	(.0000)	(.0015)	(.0033)	(.0005)	(.0002)	(.0003)	(.0001)
Female	-.0134**	-.0022*	-.0429	-.0013	-.0275	-.0089	-.0506*	-.0155*
	(.0063)	(.0012)	(.1075)	(.0033)	(.0288)	(.0095)	(.0434)	(.0132)
Sole_Prop	.0228	.0082	-.8339	-.0254***	-.2112**	-.0686*	-.1845**	-.0567**
	(.0193)	(.0070)	(.3924)	(.0038)	(.1129)	(.0388)	(.0974)	(.0297)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-.1483		-2.643***		-.4852***		.7379**	
	(.1785)		(.3750)		(.1366)		(.3876)	
Selection equation instrument								
Sales_Decline	.1778***							
	(.0320)							
Supplier Credit			.0032*					
			(.0019)					
Mgr time					.0057**			
					(.0016)			
Crime							.1017*	
							(.0428)	
Wald test Prob>chi2	.0618		.0108		0.000		0.000	
Observations	3568		3030		2464		2464	

Notes: The variables used in this table are defined in the notes to Table 1 and are not included for brevity. The variables Sales_Decrease, Supplier Credit, Mgr Time and Crime are defined in the Data and Method section. *, ** and *** signify significance at the 10 %, 5 % and 1 % levels, respectively. Standard errors are clustered by country.

Table 3
High-level technology in production and female ownership.

	Credit apply		Credit approved		Collateral		Large loan	
	Probit	***Marginal***	***Probit***	***Marginal***	***Probit***	***Marginal***	***Probit***	***Marginal***
Technology	-.1832***	-.0674***	.2316***	.0033***	.0241	.0071	.5140**	.0941**
	(.0358)	(.0137)	(.0580)	(.0008)	(.0481)	(.083)	(.1029)	(.0335)
Female	.0003	-.0002	-.0394	-.0006	-.0281	-.0086	-.1636	-.0301
	(.0153)	(.0066)	(.1178)	(.0018)	(.0634)	(.0198)	(.1615)	(.0967)
Technology# Female	-.0354	-.0130	.0720***	.0021***	-.0245	-.0068	.1749**	.0322**
	(.0283)	(.0103)	(.0110)	(.0001)	(.0869)	(.0266)	(.0899)	(.0091)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-.2168		4.251***		-.2969**		-1.036	
	(.1845)		(.9721)		(.1554)		(3.202)	
Selection equation instrument								
Sales_Decline	.1779***							
	(.0329)							
Supplier Credit			.0029					
			(.0018)					
Mgr time					-.0017			
					(.0038)			
Crime							-.0215	
							(.0416)	
Wald test Prob>chi2			0.000		0.000		0.000	
Observations	3568		3030		2464		2464	

Notes: This table displays the results of the interaction of whether a firm is female-owned and the level of technology on applying for credit, getting credit approved, the requirement for collateral and the loan size. The variables used in this analysis are detailed in Table 1. *, ** and *** signify significance at the 10 %, 5 % and 1 % levels, respectively. Standard errors are clustered by country.

robots, and advanced manufacturing processes. Aligning with the baseline regression, Table 4 indicates that having CNC, robots and advanced technology in the production process positively impacts the firm level of credit approval and loan size.

Recent finance studies use propensity scores to minimise the effects of confounding when using observational data. Our Propensity Score Matching (PSM) results for firms using high-level technology in the production process (Technology = 1) and not (Technology = 0) are reported in Table 5. Aligning with the main findings, Table 5 indicates that the effect of high-level technology in firm manufacturing processes has a negative impact on applying for credit and a positive impact on loan approval and loan size.

Table 4
Technology types and credit access.

Panel A: The impact of CNC machines in the production process on funding characteristics								
	Credit apply		Credit approval		Collateral		Large loan	
	Probit	Marginal	Probit	Marginal	Probit	Marginal	Probit	Marginal
CNC	-5.807***	-.1075***	.8116*	.0476*	.0173	.0055	-.2625	-.0416
	(.1446)	(.0132)	(.7395)	(.0160)	(.1223)	(.0382)	(.404)	(.1438)
Control variables	Yes	Yes	Yes	Yes	Yes		Yes	
Cons	-3.212***		3.478**		-1.100		1.361	
	(.4326)		(1.978)		(1.348)		(2.553)	
Selection equation instrument								
Sales_Decline	.0666**							
	(.0222)							
Supplier Credit			.0030*					
			(.0017)					
Mgr time					-.0022**			
					(.0011)			
Crime							-.0223	
							(.0422)	
Wald test Prob>chi2	0.000		0.005		0.000		0.3863	
Panel B: The impact of robots in the production process on funding characteristics								
	Credit Apply		Credit Approval		Collateral		Large Loan	
	Probit	Marginal	Probit	Marginal	Probit	Marginal	Probit	Marginal
Robot	-.5056	-.0122	1.513**	.6999**	.2771	0892	.1997**	.0299**
	(.4442)	(.0096)	(.7656)	(.1814)	(.2271)	(.1271)	(.0233)	(.0092)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-.9891***		3.661**		-1.087		-1.406	
	(.1484)		(1.419)		(1.294)		(2.507)	
Selection equation instrument								
Sales_ Decline	.0667**							
	(.0222)							
Supplier Credit			.0030*					
			(.0017)					
Mgr time					-.0022**			
					(.0010)			
Crime							-.0222	
							(.0410)	
Wald test Prob>chi2	0.0552		0.0136		0.0633		0.085	
Panel C: The impact of advanced technology in the production process on finding characteristics								
	Credit apply		Credit approval		Collateral		Large loan	
	Probit	Marginal	Probit	Marginal	Probit	Marginal	Probit	Marginal
Advanced Tec	-6.071***	-.0949***	.8116***	.0476***	-.0092	-.0029	.0367	.0054
	(.1341)	(.0119)	(.0739)	(.0166)	(.1785)	(.0565)	(.1730)	(.0448)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-3.233***		3.709***		6.414**		9.198*	
	(.4392)		(.8035)		(.2285)		(.3817)	
Selection equation instrument								
Sales_ Decline	.0667***							
	(.02234)							
Trade Credit			.0030**					
			(.0017)					
Mgr time					-.0022**			
					(.0011)			
Crime							-.0223	
							(.0440)	
Wald test Prob>chi2	0.000		0.000		0.000		0.000	

Notes: This table shows the results of the relationship between technology and finance. Panel A identifies the effect of the use of CNC machines in a firm's production processes. Panel B displays the results of whether a firm extensively uses robots in their production processes, while Panel C shows the results of the use of advanced technologies in a firm's production processes. The variables used in this analysis are the same as previously and are detailed in Table 1. *, ** and *** signify significance at the 10 %, 5 % and 1 % levels, respectively. Standard errors are clustered by country.

4. Conclusion

This paper presents results on the relationship between technological advancements in the manufacturing sector and the capacity of firms to secure external financing. Our results demonstrate that technology adoption in the production process has a positive impact on credit approval. Additionally, firms with a high level of technology in the production process are more likely to get a large loan. Further, we find that the technology adaptation reduces the gender gap in credit approval and loan size.

The results presented in this paper provide significant implications. The manufacturing industry provides great support to a country's economy and technology innovations provide efficiency gains over non-technological counterparts. As such, governments can tailor support mechanisms via direct monetary support or advisory to increase the application rate, acceptance rate and speed of access to external finance. From a firm perspective, this research highlights that while there may be barriers in the application process for those that are technologically advanced, the likelihood that finance is approved is higher and the firm may be able to expand quicker via larger loans.

We explore the interaction between technology adoption and external finance for manufacturing firms, however, our analysis could be expanded to investigate a broader range of industries that have technological innovations. Further studies could investigate the evolution of the adoption of technologies within multiple sectors to identify the long-run changes in the ability of these firms to obtain finance. The current cross-sectional dataset limits the ability to establish causal relationships between technology adoption and access to finance. Hence, future studies can use panel data or quasi-experimental designs to better identify causal effects.

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CRediT authorship contribution statement

Nirosha Wellalage: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Damien Wallace:** Writing – original draft, Conceptualization. **Krishna Reddy:** Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare no conflicts of interest related to this work.

Appendix

Country name	GDP per capita in USD *	Global Innovation index	Robot density in the manufacturing industry 2022**
Austria	52,085	7	219
Belgium	49,927	26	216
Denmarks	67,790	10	274
Finland	50,872	9	-
France	40,886	12	180
Germany	48,718	8	415
Ireland	103,983	23	-
Luxembourg	125,006	19	-
Netherland	57,025	5	248
Sweden	56,424	3	343

Table 5
Propensity score matching results.

Credit apply	Coefficient	Std.Err	P > |z|
ATE	-.0033	.0062	.059
Technology or not (1 vs 0)			
Credit approval			
ATE	.0017	.0201	.032
Technology or not (1 vs 0)			
Collateral			
ATE	.0014	.0278	.598
Technology or not (1 vs 0)			
Large loan			
ATE	.0113	.0197	.056
Technology or not (1 vs 0)			

Source: World Development Indicators and Global Innovation Index (The World Bank 2022, and 2023, respectively).
International Federation of Robotics.
** Average Europe: 136 (EU 208).

Data availability

No data was used for the research described in the article.

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