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When businesses go digital: The role of CEO attributes in technology adoption and utilization during the COVID-19 pandemic

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ABSTRACT

COVID-19 has prompted a rush of technology adoption as businesses turned to digital technologies to avert closure in the face of an unprecedent pandemic. This study examines the adoption and utilization of e-commerce and remote work technologies among small and medium enterprises (SMEs) during the pandemic. Building on various streams of research on technology adoption and utilization, we elaborate how CEO gender and experience can shape risk-taking attitude and crisis responsiveness, influencing technology adoption and utilization decisions. Analysis using a rich dataset of >20,000 enterprises across 42 countries revealed that female CEOs were significantly less likely to adopt remote work technologies; moreover, female CEOs leading small-sized enterprises were less likely to adopt e-commerce. However, CEO gender was not associated with the utilization intensity of remote work and e-commerce technologies. CEOs' industry experience was found to have an inverted U-shaped relationship with the adoption and utilization of both e-commerce and remote work technologies. These results reveal that top management decisions attributable to CEO experience, and to a lesser degree to CEO gender, can help explain divergent levels of digital technology adoption and utilization during the pandemic.

1. Introduction

Major crises tend to disrupt the status quo by instantiating new ways of conducting business, and COVID-19 has not been an exception to this rule. After the novel coronavirus was declared a pandemic by the World Health Organization on March 11, 2020 (Belhadi et al., 2021), governments around the world started to implement lockdown policies that forced businesses to resort to ICT for conducting their daily operations, spawning a level of digital transformation that would normally take a decade to realize (OECD, 2021). To ensure business continuity in the face of unprecedented disruptions, enterprises around the world have espoused processes like e-commerce, remote work and robotization. A resort to digital technologies made it possible to conduct business remotely in the face of public health policies that restricted mobility and closed work places (Birhanu et al., 2022).

This rapid uptake in digital technologies could give adopters a lasting competitive edge by positioning them for growth and market leadership (Akpan et al., 2022). Digital technologies can provide building blocks for dynamic capabilities (Belitski et al., 2022) that enable companies to redefine their business models by overhauling obsolete organizational practices and replacing them with new, innovative ones (Carillo et al., 2021). Reflecting these potential gains in efficiency and competitiveness, productivity and stock price losses during the pandemic were significantly lower in skill-intensive industries that could adopt remote work technologies (Davison, 2020; Bartik et al., 2020). Moreover, digital technologies, such as those supporting remote work, can improve employee motivation and job satisfaction by increasing workers' autonomy and flexibility (Belitski et al., 2022; Kazekami, 2020). Besides, e-commerce can help expand markets by reaching new consumer segments through cost-effective means of product delivery (Brem et al., 2021; Martin and MacDonnell, 2012). Gains from improved market access and customer engagement could be especially high for SMEs, which typically experience severe market access and financial constraints (Markovic et al., 2021; OECD, 2021).

However, there were also notable heterogeneities among enterprises in adopting digital technologies (OECD, 2021). This can be partially attributed to differences in IT capabilities and complementary resources, both at firm and geographic levels, that influenced the marginal productivity of new digital technologies and the adjustment cost of rapidly adopting them (Akpan et al., 2022; Tan and Ludwig, 2016). For SMEs,

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low level of digital readiness due to limited IT capabilities and knowhow reduced demand for digital technologies (Eller et al., 2020), curtailing their ability to espouse remote work and e-commerce (Markovic et al., 2021). Apart from structural forces that influence the marginal productivity of new technologies (pull factors) and their cost and feasibility (push factors), top management attributes can also influence technology adoption decisions. Upper Echelon Theory (Hambrick and Mason, 1984) contends that individual top managers can significantly shape strategic corporate decisions, including those pertaining to technology adoption and utilization. The risk appetite of top managers, their strategies for navigating crises, and their openness for new digital technologies can influence technology adoption decisions (Knoesen and Seymour, 2020). Likewise, human capital theories (e.g., Marcati et al., 2008) and resource-based perspectives (e.g., Gómez and Vargas, 2012) suggest that the top management skill endowments can serve as intangible resources that complement new technologies, thus influencing their feasibility and economic value (e.g., Gómez and Vargas, 2012).

Emerging evidence suggests that the effects of COVID-19 on smaller enterprises operated through channels that are idiosyncratic to owners and managers, such as perturbations in the work-life interface of top managers during the pandemic (Birhanu et al., 2022). Nonetheless, the extent to which top management attributes shaped technology adoption during the pandemic is not yet fully understood. There is particularly limited research effort to understand the factors behind apparently limited technology uptake among small and medium enterprises during the pandemic (Markovic et al., 2021). This study aims to bridge this gap by examining the role of CEO attributes, in particular gender and experience, on the adoption and usage of digital technologies during the COVID-19 pandemic among small and medium businesses. Building on various streams of research on top management characteristics and behavioral perspective of innovation research (Scoresby et al., 2021; Strohmeyer et al., 2017; Roy and Sarkar, 2016), we argue that variations in top management attributes could potentially explain divergences in new technology investments (adoption) and the intensity of usage in existing digital technologies (utilization). In particular, we hypothesize that female CEOs exhibit different behaviors in terms of risk-taking attitude and crisis responsiveness that would make them less likely to adopt and utilize remote work and e-commerce technologies. Further, we contend that the effect of CEO experience on technology adoption will be positive but diminishing since high experience could create a legacy effect that reduces risk appetite (You et al., 2020; Roy and Sarkar, 2016). Experience will also have a diminishing value in informing responsiveness to an unprecedented crisis, resulting in an inverted U-shaped relationship between CEO experience and technology adoption and utilization during the pandemic.

We test these hypotheses using the World Bank's COVID-19 tracking dataset that covers >20,000 enterprises across 42 countries, 80 % of which are SMEs. The results reveal that female CEOs were less likely to adopt remote work technologies during the pandemic; moreover, female CEOs leading small sized enterprises were less likely to adopt e-commerce. However, there is no statistically significant association between the gender of CEOs and the intensity of utilization of these technologies. Further, CEOs' experience has the expected inverted U-shaped relationship with the adoption and utilization of e-commerce and remote work technologies.

The study makes three contributions to the literature. *First*, it provides new evidence on technology adoption and utilization in SMEs during the pandemic. Past research has generally overlooked the topic of technology usage in small and medium enterprises (SMEs) (Markovic et al., 2021) although they fared poorly in adopting and integrating digital technologies (Eller et al., 2020). Using a large dataset of firms dominated by SMEs, the study documents how female leadership in businesses interacts with firm size, contributing to a "liability of smallness" that reduces e-commerce adoption (Cenamor et al., 2019). *Second*, the study enriches research into technology adoption and utilization by providing granular insights on the role of managerial attributes in shaping technology usage decisions in an uncertain environment. By documenting how enterprises leveraged specific digital technologies to overcome business disruptions caused by COVID-19, this study extends prior research on technology adoption that tended to provide generic explanations without taking into account context-relevant contingencies (Ollo-López et al., 2020; Carillo et al., 2021). *Finally*, the study integrates insights from diverse streams of research to shed light on the microfoundations of digital technology adoption and utilization. By explicating how the attributes of top managers shape technology adoption decisions, it demonstrates how the actions of powerful individuals influence business-level outcomes (Barney and Felin, 2013; Storbacka et al., 2016).

The rest of the manuscript is organized as follows. The next section sketches the patterns and drivers of digital technology adoption during the COVID-19 pandemic. Section Three introduces our theory and hypotheses while Section Four describes our data and methodology. Section Five presents the results, followed by Section Six that concludes the paper by discussing research implications, limitations and future research directions.

2. Digital technology adoption during COVID-19

The COVID-19 pandemic has catalyzed a widespread adoption of digital technologies in business, especially in the domains of e-commerce and remote work. At the onset of the pandemic in spring 2020, about half of the US workforce was working from home (Brynjolfsson et al., 2020) – a ten-fold increase in the number of people who worked remotely relative to the pre-pandemic period (Carillo et al., 2021; Ollo-López et al., 2020). In advanced economies, up to 70 % of businesses increased their use of digital technologies although most of the new adopters are larger firms (OECD, 2021). These trends also persisted a year after the pandemic started, suggesting a lasting transformation in the nature of work that made digital technologies central to core business operations (Carillo et al., 2021). However, not everyone was an equal participant of this transformation. The radical shift towards digital technologies came at a time when many businesses, especially SMEs, were unprepared for such a change. Emerging research is seeking to establish the conditions under which SMEs were able to effectively integrate digital technologies to remain resilient and competitive during the pandemic (Eller et al., 2020).

The literature on technology diffusion identifies three sets of factors that can help understand differences in technology adoption and utilization: *demand conditions*, *supply conditions*, and *managerial attributes* (Lashitew et al., 2019). Demand (pull) conditions are those factors that influence the attractiveness of different digital technologies during the pandemic. Greater demand for digital technologies can result from stronger IT capabilities and complementary human capital that increase the marginal productivity of technologies assets (Akpan et al., 2022; Gómez and Vargas, 2012). Remote work, for example, had greater demand in knowledge-intensive industries (e.g., corporate services and information technology) rather than in capital-intensive sectors such as manufacturing, as well as among multinationals and other companies with international clientele (Fischer et al., 2021). Moreover, demand for virtual service delivery varied across sectors and geographies depending on the severity of the pandemic, stringency of public health polices (Birhanu et al., 2022), and the degree of disruptions in supply chains (OECD, 2021). For example, e-commerce and home delivery were widely used by businesses in retail and catering sectors, especially by restaurants that were shuttered by social distancing laws. Overall, enterprises that had built up their ICT capabilities and other complementary resources (Cenamor et al., 2019; Muninger et al., 2019) had significant digital readiness that enabled them to seamlessly transition to a new, remote-work environment (Brem et al., 2021; Krammer, 2022; Fischer et al., 2021).

Supply (push) factors are mainly industry- and country-level conditions related to the availability of ICT infrastructure and relevant digital

solutions. Successful use of e-commerce and remote work requires widespread access to basic ICT infrastructure and sufficient exposure to internet-based services among workers, consumers, and other market participants (OECD, 2021). A well-developed ICT infrastructure leads to extensive availability and use of computers, tablets, smartphones and other devices that facilitate remote work and e-commerce (Fischer et al., 2021). On the other hand, a poorly-developed ICT infrastructure that constrains communication inhibits effective use of ICT for virtual delegation of authority (Ollo-López et al., 2020). The role of digital infrastructure in e-commerce adoption has been widely documented, especially in developing countries where these constraints inhibit firm innovation (Akpan et al., 2022; Tan and Ludwig, 2016).

Beyond demand and supply forces, the characteristics of top managers play a vital role in determining discretionary technology adoption decisions. What is called "Upper Echelon Theory" of management (Hambrick and Mason, 1984) posits that organizational outcomes are significantly shaped by strategic decisions made by individual top managers. CEOs and other senior managers make decisions by sensing, analyzing and seizing business opportunities and challenges – a process that is a function of the managers' personality traits, age, gender, experience, skill, and values (Hambrick and Mason, 1984). Individual managers' preferences, expectations and attitudes thus find a way to influence the course of adoption and utilization of new technologies (Barney and Felin, 2013; Storbacka et al., 2016). Moreover, research in innovation studies underscores the importance of key managerial actors or "champions" who vouch for the creation, adoption and utilization of innovations. Such managers put themselves on the line for an idea of doubtful success, supporting innovation through their enthusiasm, confidence, persistence, and their ability to bring the right people together (Mansfeld et al., 2010).

Since new technologies often face opposition from entrenched actors with vested interest in the status quo, the presence of top managers and CEOs who champion new technologies is critical for their successful implementation (Goepel et al., 2012). Top managers who actively champion new technologies will help overcome uncertainties, garner the support of low and middle level managers, and ensure the allocation of sufficient resources for implementing new technologies. In line with this, prior research has pointed to the key role of managerial attitudes in determining the adoption of digital technologies (Tokarchuk et al., 2021). Managers that valued work-life balance, for example, were more likely to endorse remote work technologies (Fischer et al., 2021). Equally important is the extent to which managers expect workers to be responsible and self-reliant while working from distance (Fischer et al., 2021). The following section will build on these insights to elaborate how the gender and experience of CEOs influence their technology adoption decisions.

3. Hypotheses

This section puts forward a set of hypotheses relating CEO attributes to digital technology adoption and utilization during the COVID-19 pandemic. Both technology adoption and utilization reflect enterprise responses in the face of an unprecedented public health crisis and an economic disruption. Technology adoption captures new investments in acquiring and deploying digital technologies, which can be both risky and costly – especially in the context of a global pandemic and an ensuing economic fallout. Technology utilization, on the other hand, reflects measures by enterprises to deploy or repurpose existing technologies to mitigate business closure during the pandemic. At a fundamental level, both measures of technology usage are underpinned by the same underlying forces related to demand (pull) forces, supply (push) forces and CEO attributes (Kurzhals et al., 2020; Lashitew et al., 2019). However, the relative significance of these explanatory factors could diverge since technology adoption and utilization entail different levels of risk, cost, and implementation difficulty, which makes it necessary to treat them separately while analyzing their drivers.

3.1. The role of CEO gender in technology adoption and utilization

Investing on digital technologies in the midst of an economic and health crisis necessarily requires a willingness to bear a relatively high level of risk. Moreover, introducing novel digital technologies necessitates responsiveness and adeptness to change since these innovations entail rewiring organizational processes and breaking established managerial practices. Adopting remote work, for instance, entails abandoning direct supervision and monitoring in favor of loose, virtual coordination and output-based performance assessment (Tokarchuk et al., 2021). Likewise, introducing e-commerce involves espousing novel processes of supply chain coordination and customer engagement. As these technologies have several transformative aspects, successfully adopting and integrating them into organizational practices will require a certain level of risk-taking attitude and managerial adaptability. Given these conditions, CEO attributes like gender and experience that influence risk attitude and managerial adaptability can play an important role in determining the adoption of these technologies.

Prior research suggests that gender is an important predictor of risk attitude, with women CEOs exhibiting greater risk-aversion than men CEOs. For example, Faccio et al. (2016) found that female CEOs run less risky firms, measured in terms of leverage, earnings volatility, and length of lifespan. The study also found that transitions from male to female CEOs were associated with an economically and statistically significant decline in corporate risk-taking. A large body of experimental evidence provides backing to the hypothesis that women have less appetite for risk-taking and competition (Croson and Gneezy, 2009). In the context of COVID-19, the study of Tønnessen et al. (2021) among Norwegian knowledge workers showed that female workers tended to engage in external digital knowledge sharing programs more than men workers did. Analysis of employment data from 10 developing countries by Wu (2022) documented that the proportion of female workers declined significantly after the onset of the pandemic.

The relationship between gender and risk taking is likely to be nuanced and contingent on a range of organizational and contextual factors (You et al., 2020).[1] For example, the tendency of risk aversion among female CEOs could be particularly high during times of crises and uncertainty. Cesaroni et al. (2015) report that, during a time of economic and financial crisis in Italy, female entrepreneurs were more likely to adopt defensive measures aimed at guaranteeing business survival through efficiency improvements, restructuring and downsizing. By contrast, male entrepreneurs were more likely to adopt offensive strategies, including new investments and innovation for strengthening medium- and long-term competitive advantage (Cesaroni et al., 2015).

Some scholars attribute these differences in risk-taking attitude to underlying behavioral differences between men and women on how they see the world and respond to stress and external shocks. According to this view, men tend to interpret risky situations as challenges that stimulate active participation, while women tend to interpret them as threats that need to be avoided or reduced (Cesaroni et al., 2015). Men demonstrate agentic qualities that are relevant for goal attainment such as assertiveness, aggression and autonomy while women exhibit prosocial and communal qualities such after expressiveness, connectedness, kindness, and caring (Yu and Chen, 2016). There is also some evidence that emotion plays a role here – women tend to experience stronger affective reactions, such as fear and anger, in the event of negative outcomes, which potentially reduces their risk appetite (Croson and Gneezy, 2009). Moreover, greater risk-taking among men could be related to their overconfidence in their own abilities, an attribute in

[1] In line with this contingency view, Saggese et al. (2021) found that female CEOs spend more on R&D when their board also has a critical mass of women directors. Farag and Mallin (2018) also found no significant relationship between gender and risk taking in their analysis of a panel dataset of Chinese firms.

which they score significantly greater than women (Croson and Gneezy, 2009). There are, however, critiques against providing definitive explanations in favor of stable gender differences. Such views contend that the dichotomy between risk-taking and risk-aversion, or between offensive and defensive responses, is stereotypical and oversimplifying (Manolova et al., 2020).

Nonetheless, relatively small differences in risk attitudes and preferences between the genders (Rink et al., 2012) could be amplified through rigid societal norms that lead to differentiated educational choices and employment experiences (Strohmeyer et al., 2017). Societies ascribe different gender roles and identities to men and women in communal and occupational environments (Branzei and Abdelnour, 2010). Patriarchal norms that differentially encourage and reward different types of behavior in men and women (Glass et al., 2016) could perpetuate the observed proclivity of girls to study social rather than natural sciences. Women business leaders thus end up with limited experience in science and technology fields (Baron et al., 2007), which in turn will limit their ability to take risky decisions that espouse radical innovation. Likewise, when girls are socialized to be agreeable and have a concern for others (Rink et al., 2012), the outcome could be female leadership that is conservative, and reluctant to challenge and transform established business practices. Women CEOs could thus settle for incremental innovations that conform to traditional practices (Strohmeyer et al., 2017) rather than pursuing radical innovations that can significantly transform current working patterns.

Finally, the unique set of circumstances that women CEOs encountered during the pandemic could limit their ability to respond to the crisis by adopting new digital technologies. As in other economic downturns and natural disasters (Manolova et al., 2020), COVID-19 had a significantly greater adverse effect on women entrepreneurs. Female owned enterprises were closed for a significantly longer period of time and registered significantly lower sales growth compared to male owned ones (Birhanu et al., 2022). This is partly because female workers and entrepreneurs were severely affected by the closure of schools and daycare centers, which massively increasing child care needs at the cost of reduced working hours (Alon et al., 2020; Collins et al., 2021). Already resource-constrained, female-led/owned small businesses suffered from liquidity shortages as financial and public institutions tended to prioritize rationing resources to strategically important and politically-connected large firms (Birhanu et al., 2022; Kubinec et al., 2021). These challenges are likely to limit the ability of female-run businesses to respond to the pandemic by adopting and utilizing new digital technologies.

Hypothesis 1a. Businesses with female CEOs will be less likely to adopt digital technologies during the COVID-19 pandemic.

Hypothesis 1b. Businesses with female CEOs will have lower utilization of digital technologies.

3.2. The role of CEO experience in technology adoption and utilization

Risk attitudes could differ across managers for simple exogenous factors, such as age, gender and testosterone levels, or for more complex contingencies related to the business environment (Apicella et al., 2015). Young managers generally have limited established job credentials, so they will be more willing to explore new opportunities by taking risks in an effort to test or prove their competence (You et al., 2020). Having little to lose but much to gain, they will have high motivation to shake or break rules so long as they can lead to superior performance.

Highly experienced managers, on the other hand, could be reluctant to abandon their deeply-ingrained managerial style in favor of new ones, such as those that rely on ICT for coordinating business operations (Scoresby et al., 2021). With experience, managers accumulate rich relationships and legacies that need to be maintained and defended, which reduce their autonomy of action and inhibit risk-taking. Perceived loss of control and the need to avoid uncertainties could thus discourage experienced managers from boldly investing on disruptive technologies (Hopp et al., 2018). They would rather adopt incremental changes that maintain the status quo instead of experimenting with novel innovations that could undo their legacy (Assink, 2006). Unfortunately, historical experience cannot be an effective guide for finding solutions in a highly ambiguous and uncertain episode such as a pandemic. Effective use of e-commerce, for example, will require pathbreaking efforts of experimentation to upend traditional ways of doing business and discover as-yet unrealized customer needs. There is some evidence confirming that high work experience can indeed reduce risk aptitude. Farag and Mallin (2018) found that younger and short-tenured CEOs were more likely to consider risky decisions, where risk is approximated by the standard deviation of daily stock returns for each year.

Experience can also affect technology adoption decisions through its influence on managers' *responsiveness* to crises (Chan et al., 2019). Even when experienced managers could sense new business opportunities (Fischer et al., 2021), their openness to respond by adopting new and radical innovations is likely to dwindle as experience exceeds a certain threshold (You et al., 2020). In large part, this is because of the increased difficulty to unlearn obsolete mental models and adopt novel business concepts (Hopp et al., 2018). The ability to shed archaic mental models is a critical element of higher-order learning (meta-learning), whereby people and firms systematically discard outdated systems of meaning and substitute them with something fundamentally new (Assink, 2006). The inhibitive role of obsolete mental models, and the challenge to update them, has been documented among established corporations that have outlived their success formula (Hopp et al., 2018). Among individual managers, who have a shorter life/tenure span, this mental effect is likely to be even greater – an individual manager can only do so much to reinvent herself and learn entirely new skillsets in her golden days. In the face of turbulent environments, managers who do not know what they need to know will have limited ability to correct their course, and can fall prey to irrational behaviors such as avoidance, indecision and insularity (Assink, 2006).

Seeking stability, structure and efficiency, highly experienced managers will respond to crises by following familiar pathways that proved effective in the past – a phenomenon that has been dubbed "the tyranny of success" or "the incumbent's curse" (Roy and Sarkar, 2016; Cenamor et al., 2019). In drastically new environments, however, time-tested routines and competencies can become learning traps that constrain fresh thinking. During the uncertainties of an unfolding pandemic, heavy reliance on past experience could reduce the ability of managers to envision and enact novel approaches to configure organizational resources to match unanticipated challenges. Long experience can thus become a liability and determinantal to innovativeness in the face of rampant uncertainties. In contrast, managers with moderate experience could be less burdened by history and less bound by old mental models, and thus have greater bandwidth to envision, sense, and seize new solutions.

In sum, the effect of CEO experience on technology adoption and utilization is likely to be positive, but with a diminishing effect. A moderate level of industry experience can improve the ability of managers to properly weigh the benefits and risks of new technologies, helping them to avoid predictable strategic pitfalls. High levels of experience, however, could be attended by "legacy" effects that reduce risk-taking, constrain agility, inhibit higher-order learning, and lower innovative responsiveness, especially during times of turbulent shocks like a pandemic. We conclude that CEO experience will improve the ability of managers to adopt and utilize novel technologies only to a certain threshold, after which its effect will diminish, as indicated in the following hypothesis.

Hypothesis 2a. CEO experience has an inverted U-shaped relationship with the adoption of digital technologies during the COVID-19 pandemic.

Hypothesis 2b. CEO experience has an inverted U-shaped relationship

with the utilization of digital technologies.

4. Data and methodology

4.1. Data and variables

We tested our hypotheses using cross-sectional survey data of >20,000 enterprises across 42 countries from the World Bank's ongoing *COVID-19 Tracking Survey*. This novel dataset is dominated by small and medium enterprises with <100 employees, which make up 80 % of the sample. The data was collected over the period of April 2020 – March 2021 and tracks innovation adoption and utilization over the same time period. The *COVID-19 Tracking Survey* uses the same sample of firms as the *World Bank*'s *Enterprise Survey* (WBES), which is a comprehensive survey dataset that has been collected since 2006. We matched the *COVID-19 Tracking Survey* with the WBES, which provided us with an extensive number of control and other relevant variables for the pre-pandemic period.

Table 1 summarizes the measurement of variables and their data source. Here we briefly recap the measurement of key variables used in the analysis.

4.1.1. Dependent variables

We used four metrics to measure the adoption and utilization of two digital technologies: e-commerce and remote work. The adoption of these technologies is measured as follows:

(i) *E-commerce adoption* is a binary variable that gets a value of one when the business indicates that it had started or expanded selling its products and services online.
(ii) *Remote work adoption* is a binary variable that gets a value of one when the business indicates that it had started or expanded remote work.

We measure technology utilization as follows:

(i) *E-commerce utilization* is a continuous variable that indicates the percentage share of the firm's sales revenues from online sales during the pandemic.
(ii) *Remote work utilization* is a continuous variable that indicates the percentage share of the firm's workforce that works remotely during the pandemic.

4.1.2. Independent variables

Our two independent variables measure CEO attribute with respect to gender and experience. "Female CEO" gets a value of one when the top manager or CEO of the firm is female, and zero otherwise. "CEO experience" measures the number of years the CEO worked in the industry (see Table 1).

4.1.3. Control variables

We obtained a number of control variables from the matched WBES dataset, based on surveys over 2017–2019. We control for firm characteristics using size dummies identifying small (< 20 workers), medium (20–99 workers), and large (100 or more workers) enterprises, firm age, export status, foreign and public ownership, and industry dummies. We also include a number of variables that reflect supply and demand related drivers of technology adoption and utilization.

We use two variables to account for differences across firms in the supply or provision of ICT infrastructure. The first variable ("ICT Constraints") indicates the extent to which telecommunications and electricity shortage constitute important operational constraints for the business. The second ("Internet Access") is a dummy variable that indicates whether or not the firm uses internet in its operations. We control for two sets of demand factors that could influence the attractiveness (or marginal productivity) of digital technologies. The first is the degree of exposure to the pandemic, measured using a variable called "Business Closure" that indicates the number of weeks the firm was forced to close since the pandemic started. The second set of demand factors includes firm-specific technological capabilities that can complement digital technologies (Gómez and Vargas, 2012; Marcati et al., 2008). To account for differences in these capabilities, we included three dummy variables measuring different aspects of innovativeness that indicate: (i) engagement in research and development; (ii) introduction of new products and services, and; (iii) acquisition of an internationally-recognized quality certification (see Table 1). We expect that these complementary capabilities would improve the marginal return of digital technologies, so that companies that employ them will also be more

Table 1
Variable definition and measurement.

Variable	Definition
Dependent variables	
E-commerce adoption (binary)	This is a binary variable that gets a value one when the firm responds positively to the question: "Did this establishment start or increase online business activity in response to the COVID-19 outbreak?"
E-commerce utilization (% sales)	This is a continuous variable capturing the response to the following survey question during the pandemic: "Currently what is the share of this establishment's online sales out of total sales?"
Remote work adoption (binary)	This is a binary variable that gets a value one when the firm responds positively to the question: "Did this establishment start or increase remote work arrangement for its workforce due to the COVID-19 outbreak?"
Remote work utilization (% workforce)	This is a continuous variable capturing the response to following survey question during the pandemic: "Currently what is the share of this establishment's workforce working remotely?"
Independent variables	
Female CEO	This is a binary variable that gets a value of one when the firm's CEO is female and zero otherwise
CEO experience	Indicates the CEO's industry experience in years
Control variables	
ICT constraints	This is a Likert-type variable based on responses to questions that ask the extent to which telecommunications or electricity constituted obstacles to business operations
Internet access	It is a binary variable that gets a value of one when the firm has its own website, social media page or uses e-mail for communication, and zero otherwise
Business closure	Measures the number of weeks in which the establishment was closed due to the COVID-19 outbreak
New products/services (binary)	It is a binary variable that gets a value of one when the firm has introduced new or improved product/services in the past three years, and zero otherwise
Quality certification (binary)	Binary variable that gets a value of one when the firm has received an internationally-recognized quality certification in the past three years, and zero otherwise
R&D expend. (binary)	Binary variable that gets a value of one when the firm has spent money on research and development, either in-house or contracted with other companies, excluding market research surveys in the past year.
Size	Firm size is captured with three variables that indicate the firm's permanent employment: • Small size firms are those with <20 workers • Medium size firms are those between 20 and 99 workers • Large firms are those with 100 or more workers
Age	Age indicates the number of years since formation
Export status (binary)	Gets a value of one when the firm earns at least a quarter of its revenues from direct or indirect exports and zero otherwise
Foreign owned (binary)	Gets a value of one when at least 10 % of the firm's share is owned by foreign companies or individuals and zero otherwise
Public owned (binary)	Gets a value of one when at least 10 % of the firm's share is publicly owned and zero otherwise

likely to adopt and utilize digital technologies during the pandemic (Cenamor et al., 2019; Muninger et al., 2019).

4.2. Descriptive statistics

Table 2 provides descriptive statistics for key variables, and their correlations with the dependent variables. In terms of technology adoption, 27 % of the firms started or increased e-commerce during the pandemic and 36 % of them made remote work arrangements. In terms of technology utilization, on average 6.9 % of sales revenues came from e-commerce transactions and 5.9 % of the labor force was engaged in remote work. The low values of these statistics demonstrate the fact that our sample is dominated by small firms, most of which are in developing countries. Average statistics for technology adoption and utilization by country are reported in Table A1 of the Appendix. Across countries, the proportion of firms that adopted e-commerce ranged between 6 % in Chad and 54 % in Russia, and the same for remote work ranged from just 1 % in Chad to 55 % in Guatemala. *E*-commerce utilization was the lowest in Chad (0.26 % of sales revenue) and the highest in Latvia (28 % of sales revenue). The two countries also have the highest and lowest level of remote work utilization: In Chad only 0.63 % of the workforce was engaged in remote work while the same in Latvia was almost 18 %.

Table A2 in the Appendix reports average statistics of technology adoption and utilization broken down by subindustry. The air transport industry has the highest rate of adoption both for e-commerce and remote work. Manufacture of transport equipment has the lowest adoption rate for e-commerce, and tanning and dressing of leather products has the lowest adoption rate for remote work. These differences indicate the relative ease of adopting remote work practices in service industries compared to manufacturing. In terms of technology utilization, air transport industries and computer related activities have the highest utilization rate in e-commerce and remote work, respectively. Manufacture of basic metals has the lowest level of e-commerce utilization and manufacture of tobacco products has the lowest level of remote work utilization, confirming the difficulty of going digital in manufacturing sectors. These differences point to the need to account for industry fixed effects in assessing the drivers of technology adoption and utilization.

The correlation statistics in Table 2 reveal that e-commerce adoption and remote work adoption are positively and significantly correlated with each other (coef. = 0.27, *p*-value = 0.00). Likewise, technology utilization in e-commerce and remote work are positively and significantly correlated (coef. = 0.28, p-value = 0.00). All but one of the measures of technology adoption and utilization are negatively and significantly correlated with CEO experience. Interestingly, the variable "female CEOs" is positively and significantly correlated with e-commerce adoption and utilization, which is the reverse of what we hypothesized. On the other hand, the variable has the expected negative relationship with remote work adoption. These relationships, however, are likely to be driven by large cross-country and cross-industry variations. We subsequently test these relationships using our regression framework that properly accounts for such variations.

4.3. Methodology

To test *Hypotheses 1a and 1b*, we estimate the following cross-sectional model that relates the gender of the CEO (*Female_CEO*) with our measures of innovation adoption and utilization (*INNOV*), while

Table 2
Descriptive statistics and correlation coefficients between key variables.

	Mean	S.D.	Min	Max	E-Commerce (binary)	Remote work (binary)	E-Commerce (% sales)	Remote work (% workforce)
E-Commerce adoption (binary)	0.27	0.45	0.00	1.00	1.00			
Remote work adoption (binary)	0.36	0.48	0.00	1.00	0.27	1.00		
					(0.00)			
E-Commerce util. (% sales)	6.94	17.69	0.00	100.00	0.44	0.18	1.00	
					(0.00)	(0.00)		
Remote work util. (% workforce)	5.91	16.47	0.00	100.00	0.17	0.39	0.28	1.00
					(0.00)	(0.00)	(0.00)	
Female CEO	0.18	0.39	0.00	1.00	0.02	−0.03	0.04	0.00
					(0.01)	(0.00)	(0.00)	(0.91)
CEO experience	20.67	11.24	1	50	−0.06	0.00	−0.06	−0.02
					(0.00)	(0.46)	(0.00)	(0.00)
ICT constraints	1.49	1.47	0.00	4.00	0.02	0.01	−0.00	−0.00
					(0.01)	(0.31)	(0.58)	(0.94)
Internet access	0.67	0.46	0.00	1.00	0.09	0.15	0.05	0.06
					(0.00)	(0.00)	(0.00)	(0.00)
Business closure	3.03	5.58	0.00	60.00	0.06	−0.02	0.04	0.04
					(0.00)	(0.00)	(0.00)	(0.00)
New products/services (binary)	0.24	0.35	0.00	1.00	0.08	0.13	0.05	0.08
					(0.00)	(0.00)	(0.00)	(0.00)
Quality certification (binary)	0.27	0.44	0.00	1.00	−0.05	0.13	−0.06	0.02
					(0.00)	(0.00)	(0.00)	(0.00)
R&D (binary)	0.13	0.33	0.00	1.00	0.04	0.14	0.02	0.07
					(0.00)	(0.00)	(0.00)	(0.00)
Small firms	0.46	0.50	0.00	1.00	−0.07	−0.21	−0.02	−0.06
					(0.00)	(0.00)	(0.01)	(0.00)
Medium firms	0.34	0.47	0.00	1.00	0.03	0.03	0.01	−0.01
					(0.00)	(0.00)	(0.36)	(0.16)
Large firms	0.20	0.40	0.00	1.00	0.04	0.22	0.01	0.08
					(0.00)	(0.00)	(0.03)	(0.00)
Age	23.70	16.38	2	207	−0.03	0.06	−0.04	−0.00
					(0.00)	(0.00)	(0.00)	(0.75)
Exporting (binary)	0.22	0.41	0.00	1.00	−0.03	0.11	−0.01	0.03
					(0.00)	(0.00)	(0.35)	(0.00)
Foreign owned (binary)	0.11	0.31	0.00	1.00	0.02	0.14	0.05	0.08
					(0.00)	(0.00)	(0.00)	(0.00)
Public owned (binary)	0.01	0.10	0.00	1.00	0.00	−0.00	−0.00	−0.00
					(0.98)	(0.89)	(0.82)	(0.59)

controlling for industry fixed effects (μ_j), and city-by-month fixed effects (μ_{ct}):

$$\mathrm{INNOV}_{ijct} = \alpha(\mathrm{Female\ \ CEO}_{ijct}) + \beta(\mathrm{X}_{ijct}) + \mu_j + \mu_{ct} + \varepsilon_{ijct} \quad (1)$$

where the subscript *i* denotes the firm, *j* its industry at 2-digit ISIC level, *c* its city of location, and *t* the year and month of data collection. The vector of control variables X includes factors that influence the supply of digital technologies (*ICT constraints* and *internet access*), pandemic-related factors that increase demand for digital technologies (*business closure*) and complementary technological capabilities that also increase demand for digital technologies during the pandemic (*R&D, product innovation*, and *quality certification*). The inclusion of business closure enables us to assess the effect of CEO attribute while keeping constant the level of economic disruption due to the pandemic. Our controls also include firm characteristics such as age, size, and dummies indicating foreign and public ownership and export status. The analysis includes hundreds of city-by-month dummies to mitigate omitted variable bias by accounting for wide-ranging differences in economic or institutional environments. This procedure is also important to account for differences in pandemic exposure and regulatory measures that tended to vary within countries and also changed over the course of the pandemic.

To test *Hypotheses 2a and 2b*, we include a squared term of CEO experience (*CEO_Expereince*), after log-transforming it to correct for right skewness:

$$\mathrm{INNOV}_{ijct} = \gamma(\mathrm{CEOExperience}_{ijct})^2 + \sigma(\mathrm{CEOExperience}_{ijct}) + \beta(\mathrm{X}_{ijct}) + \mu_j + \mu_{ct} + \varepsilon_{ijct} \quad (2)$$

We expect the coefficient of the squared term of CEO experience, γ, to be negative and significant, in line with our hypothesis that CEO experience has an inverted U-shaped relationship with technology adoption and utilization. Since the two CEO attributes, gender and experience, could be correlated with each other, we alternately include them in the regressions separately, as well as both at once.

To explain the two binary variables measuring technology adoption, we estimate Eqs. (1) & (2) using the probit model. To explain the two continuous variables measuring technology utilization, we estimate Eqs. (1) & (2) using the Ordinary Least Squares (OLS) estimator. In both cases, we cluster the standard errors within country-industry groups (Wooldridge, 2015).

5. Results

5.1. CEO attributes and technology adoption

Table 3 reports the regression results that test the effect of top management attributes on technology adoption. Since technology adoption is a binary variable, the analysis is based on the binary outcome probit model, as explained in the methodology. Regressions 1–3 are for e-commerce adoption and regressions 4–6 are for remote work adoption. For each dependent variable, the first regression includes the variable for female CEOs, the second includes experience and its squared term, and the third includes both variables at once. Regression 1 shows that having female CEOs does not have a significant effect on e-commerce adoption. This does not change when experience and its squared term are included in regression 3. However, regression 4 shows that remote work adoption is significantly lower in companies that have female CEOs, and this effect remains negative and significant in regression 6. This result provides partial support for Hypothesis 1a.

Table 3
The effect of CEO gender and experience on digital technology adoption.

	(1)	(2)	(3)	(4)	(5)	(6)
	E-commerce (binary)	E-commerce (binary)	E-commerce (binary)	Remote work (binary)	Remote work (binary)	Remote work (binary)
Female CEO	0.017		−0.002	−0.053**		−0.063***
	(0.029)		(0.030)	(0.024)		(0.024)
Log(CEO Experience)		0.274***	0.274***		0.153*	0.156*
		(0.093)	(0.093)		(0.089)	(0.090)
(Log(CEO Experience))^2		−0.063***	−0.063***		−0.044***	−0.045***
		(0.018)	(0.018)		(0.017)	(0.017)
ICT constraints	0.008	0.006	0.006	−0.000	0.001	0.001
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Internet access (binary)	0.328***	0.324***	0.324***	0.161***	0.169***	0.168***
	(0.033)	(0.033)	(0.033)	(0.029)	(0.030)	(0.030)
Business closure	0.003	0.003	0.003	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
New products/services (binary)	0.261***	0.267***	0.267***	0.184***	0.187***	0.189***
	(0.036)	(0.036)	(0.036)	(0.034)	(0.034)	(0.034)
Quality certification (binary)	−0.029	−0.031	−0.031	0.166***	0.168***	0.168***
	(0.028)	(0.028)	(0.028)	(0.033)	(0.034)	(0.034)
R&D expend. (binary)	0.041	0.032	0.033	0.198***	0.191***	0.190***
	(0.036)	(0.036)	(0.036)	(0.031)	(0.032)	(0.032)
Small size	−0.209***	−0.222***	−0.223***	−0.727***	−0.732***	−0.727***
	(0.048)	(0.047)	(0.046)	(0.061)	(0.060)	(0.060)
Medium size	−0.040	−0.062*	−0.062*	−0.418***	−0.420***	−0.418***
	(0.038)	(0.037)	(0.037)	(0.047)	(0.047)	(0.047)
Log(Age)	−0.064***	−0.028	−0.028	−0.001	0.040**	0.040**
	(0.016)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)
Exporting (binary)	−0.042	−0.049	−0.050	0.072**	0.079**	0.079**
	(0.033)	(0.033)	(0.033)	(0.031)	(0.031)	(0.031)
Foreign owned (binary)	−0.025	−0.033	−0.032	0.333***	0.321***	0.321***
	(0.036)	(0.035)	(0.035)	(0.034)	(0.035)	(0.034)
Public owned (binary)	−0.112	−0.133	−0.131	−0.239*	−0.283**	−0.278**
	(0.110)	(0.110)	(0.111)	(0.136)	(0.133)	(0.133)
Observations	21,582	20,977	20,966	21,883	21,296	21,287

Notes: All regressions are based on the probit model. City-by-month and 2-digit ISIC level industry fixed effects are included but not reported. Standard errors in parentheses have been corrected for clustering within country-sector groups.

The coefficient of female CEOs in regression 4 is −0.053, which indicates the marginal effect on the latent distribution of remote work adoption. The marginal effects of having female CEOs on the actual probability of adoption varies across observations, but its average value can be computed (Wooldridge, 2015). The average marginal effect of female ownership based on regression 4 indicates that having female CEOs is associated with a decline in remote work adoption of 4.4 % relative to the mean (−4.4 % = 100*(0.337–0.353) /0.36)). In regression 6, where we account for experience variation, the same effect is a slightly greater value of −5.3 %, indicating the importance of gender in technology adoption as indicated in *Hypotheses 1a*.

Regression 2 shows that the squared term of the log of experience is negative and significant, indicating an inverted U-shaped relation between CEO experience and the adoption of e-commerce technologies. The coefficient is unchanged when the variable indicating female CEOs is included in regression 3. Regressions 5 and 6 likewise indicate the same type of relationship between CEO experience and the adoption of remote work technologies. These results provide a strong support for Hypothesis 2a.

With respect to the control variables, ICT constraints do not have a significant effect on technology adoption. Internet access, however, has a significant positive effect as expected. Business closure also does not appear to be a significant driver of technology adoption. Firms with greater innovation capabilities, as reflected in introducing new products, quality certification and R&D engagement, are more likely to adopt digital technologies during the pandemic. However, quality certification and R&D engagement are relevant only for the adoption of remote work technologies. Small and medium firms significantly underperformed large ones (the omitted, base group) in technology adoption. Older, exporting, foreign-owned and private-owned firms are also more likely to adopt remote work technologies than their counterparts.

To get a better sense of these relationships, Fig. 1 plots the predicted probabilities of technology adoption against experience (in log form). The plot in the top panel is for e-commerce, based on regression 2, and the one in the bottom panel is for remote work, based on regression 5. Note that the predicted probabilities are close to the average values reported in Table 2 (0.27 for e-commerce and 0.36 for remote work). The predicted probability of technology adoption increases modestly as CEO experience increases but falls once CEO experience reaches a certain threshold. For e-commerce, the threshold is reached when CEO experience is nine years (i.e., 9 = exp. (2.2)). For remote work, adoption starts to fall after CEO experience reaches a lower threshold of five years (i.e., 5 = exp. (1.7)). This suggests that CEOs are more likely to adopt digital technologies when they have low to moderate levels of experience. The "optimum" level of experience needed to maximize technology adoption is far smaller than the average CEO experience in the sample, which is close to 21 years (see Table 2). In other words, most businesses tend to underperform in technology adoption because they have CEOs with too long experience.

The marginal effect of experience is also reasonably high. The probability of e-commerce adoption falls by 20 % relative to the mean as experience increases from its optimum value of 9 years to its maximum value of 50 years (−20 % = (100*(0.216–0.272)/0.27)). The probability of adopting remote work falls by 19 % relative to the mean as experience increases from its optimum value of 5 years to its maximum value of 50 years (−19 % = 100*(0.307–0.375) /0.36). These results strongly support Hypothesis 1b and highlight that long industry experience can be a liability when it comes to encouraging technology adoption.

5.2. CEO attributes and technology utilization

Table 4 reports the regression results that relate top management attributes with technology utilization. These results are easier to interpret since they are based on OLS regressions where coefficients are equal to marginal effects. With respect to gender, the variable "female CEO" is insignificant in all regressions, indicating that gender has no statistically discernible effect on technology utilization. We thus find no support for Hypothesis 2a. The squared term of CEO experience is negative and

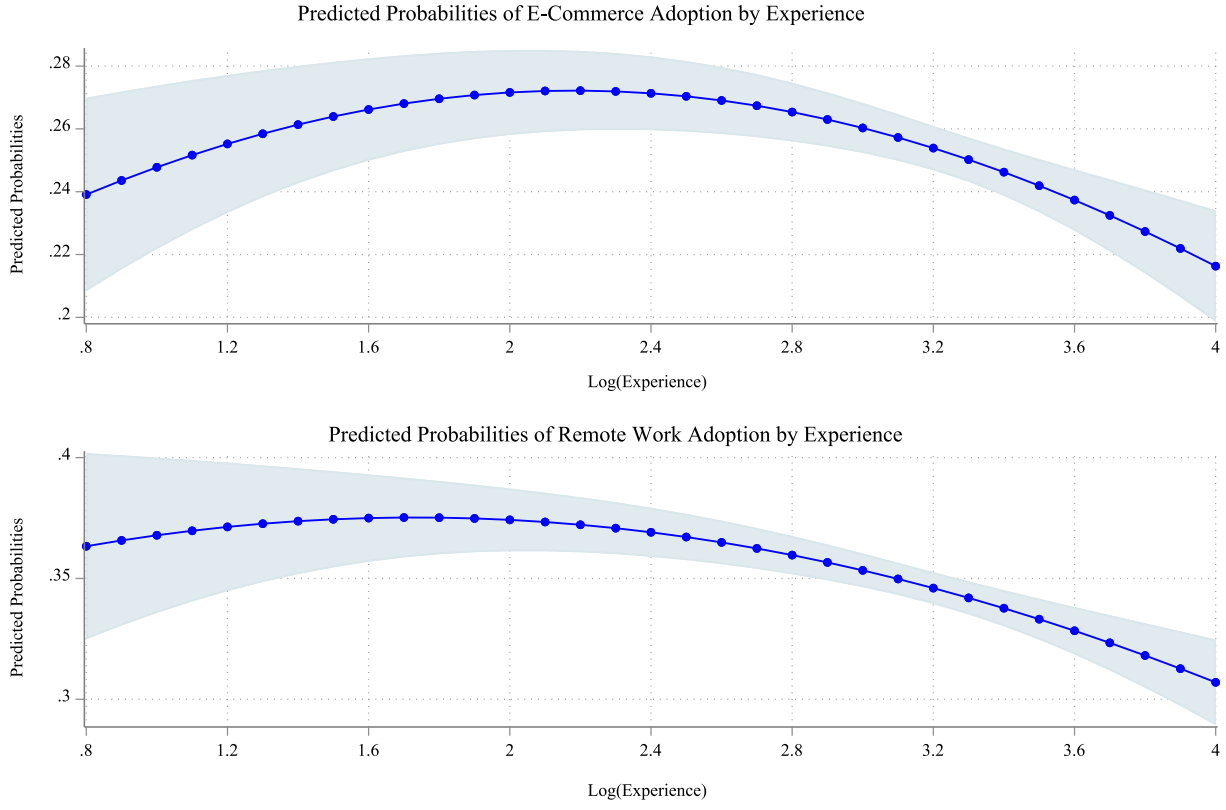

Fig. 1. Predicted probabilities of digital technology adoption at different levels of experience.

Table 4
The effect of CEO gender and experience on digital technology utilization.

	(1)	(2)	(3)	(4)	(5)	(6)
	E-commerce (% sales)	E-commerce (% sales)	E-commerce (% sales)	Remote work (% workforce)	Remote work (% workforce)	Remote work (% workforce)
Female CEO	0.180		−0.006	−0.058		−0.144
	(0.336)		(0.336)	(0.270)		(0.279)
Log(CEO Experience)		2.369**	2.378**		1.429	1.445
		(1.104)	(1.104)		(1.047)	(1.049)
(Log(CEO Experience))^2		−0.606***	−0.608***		−0.316	−0.321
		(0.216)	(0.216)		(0.199)	(0.200)
ICT constraints	−0.008	−0.021	−0.022	−0.070	−0.077	−0.078
	(0.090)	(0.093)	(0.093)	(0.085)	(0.088)	(0.088)
Internet access (binary)	2.125***	2.174***	2.179***	0.794***	0.901***	0.901***
	(0.308)	(0.308)	(0.307)	(0.273)	(0.279)	(0.279)
Business closure	0.022	0.024	0.026	0.095***	0.095***	0.099***
	(0.029)	(0.029)	(0.029)	(0.034)	(0.035)	(0.035)
New products/services (binary)	1.573***	1.652***	1.659***	1.170***	1.348***	1.359***
	(0.457)	(0.452)	(0.453)	(0.429)	(0.436)	(0.436)
Quality certification (binary)	−0.778**	−0.794**	−0.795**	0.596*	0.619*	0.623*
	(0.365)	(0.365)	(0.366)	(0.330)	(0.337)	(0.338)
R&D expend. (binary)	−0.017	−0.011	−0.014	1.126**	1.091**	1.080**
	(0.468)	(0.478)	(0.478)	(0.444)	(0.461)	(0.462)
Small size	0.417	0.373	0.370	−2.436***	−2.377***	−2.374***
	(0.459)	(0.465)	(0.465)	(0.538)	(0.550)	(0.546)
Medium size	0.629*	0.568	0.568	−1.900***	−1.853***	−1.861***
	(0.355)	(0.362)	(0.362)	(0.406)	(0.417)	(0.417)
Log(Age)	−0.475**	−0.072	−0.069	−0.204	−0.079	−0.083
	(0.205)	(0.225)	(0.225)	(0.175)	(0.190)	(0.190)
Exporting (binary)	0.895**	0.913**	0.908**	1.192***	1.213***	1.226***
	(0.412)	(0.420)	(0.418)	(0.368)	(0.380)	(0.379)
Foreign owned (binary)	1.585***	1.468***	1.470***	1.996***	1.893***	1.888***
	(0.528)	(0.536)	(0.536)	(0.505)	(0.515)	(0.515)
Public owned (binary)	−0.631	−0.930	−0.922	−0.638	−0.613	−0.594
	(1.022)	(1.034)	(1.044)	(1.054)	(1.051)	(1.059)
Observations	21,002	20,483	20,473	21,707	21,142	21,132
R-squared	0.162	0.165	0.165	0.176	0.176	0.176

Notes: All regressions are based on Ordinary Least Squares (OLS) regressions. City-by-month and 2-digit level ISIC industry fixed effects are included but not reported. Standard errors in parentheses have been corrected for clustering within country-sector groups.

significant in regressions 1 & 3, indicating an inverted U-shaped relationship with e-commerce utilization. However, the squared term of CEO experience is not significant in regressions 4 & 6, indicating lack of a robust effect on remote work utilization.

Fig. 2 plots the predicted values of e-commerce and remote work utilization against CEO experience (in log-form). The predicted value of e-commerce is maximum when CEO experience is 7.4 years (i.e., 7.4 = exp. (2)), and it is minimum when CEO experience is at its maximum (50 years). The difference between the maximum and minimum predicted values of e-commerce sales is a large 2.5 percentage points, or 36 % of its average value (36 % = 100*(7.6–5.1)/ 6.94). This represents substantial difference in technology utilization between the optimal level of CEO experience and the maximum level of CEO experience in the sample. The bottom panel of Fig. 2 plots the predicted values of remote work utilization against experience. Here too, we observe an inverted U relationship between experience and technology utilization. Although the regression coefficients for remote work are insignificant in Table 4, they are negative, which explains the inverted U-shaped relationship. Based on regression 4, the predicted value of remote work utilization is at its highest when CEO experience is 10 years. Overall, these results provide robust support for Hypothesis 2b, confirming that CEO experience has an inverted U-shaped relationship with technology utilization.

With respect to the control variables, internet access again appears as an important driver of digital technology utilization. New product introduction, foreign ownership and export all have consistently positive association with technology utilization. Interestingly, quality certification reduces e-commerce utilization but improves remote work utilization. Remote work utilization is significantly higher among firms that engage in R&D but significantly lower among small and medium-sized firms. These results reveal significant heterogeneities in the utilization of remote work and e-commerce technologies among firms.

5.3. Post-hoc test on CEO gender and firm size

The baseline analysis provides only partial support for the hypothesis that female CEOs would be less likely to adopt digital technologies (Hypothesis 1a) and no support for the hypothesis that they would utilize digital technologies less intensively (Hypothesis 1b). While these results could indicate the absence of notable differences between male- and female-led firms, they could also be driven by model specification issues. In particular, while it is possible that female-led firms in general have comparatively similar technology adoption and utilization to male-led ones, this might not be the case for smaller firms. The underlying explanations that link gender and technology adoption and utilization – especially risk attitudes – are likely to be more binding on smaller businesses that are typically financially constrained. To test this possibility, we performed additional post-hoc analysis by allowing the effect of CEO gender to interact with firm size in determining technology adoption and utilization.

The results of this analysis are reported in Table 5. Regressions 1–4 are based on the probit model and test the possibility that technology adoption is lower among smaller, female-led firms, while regression 5–8, which are based on OLS, test the same for technology utilization. The interaction term between CEO gender and small firm size is negative and significant in regressions 1 and 2. This indicates that smaller firms that are led by female CEOs are significantly less likely to adopt e-commerce technologies. In other words, the *marginal effect* of small firm size on e-

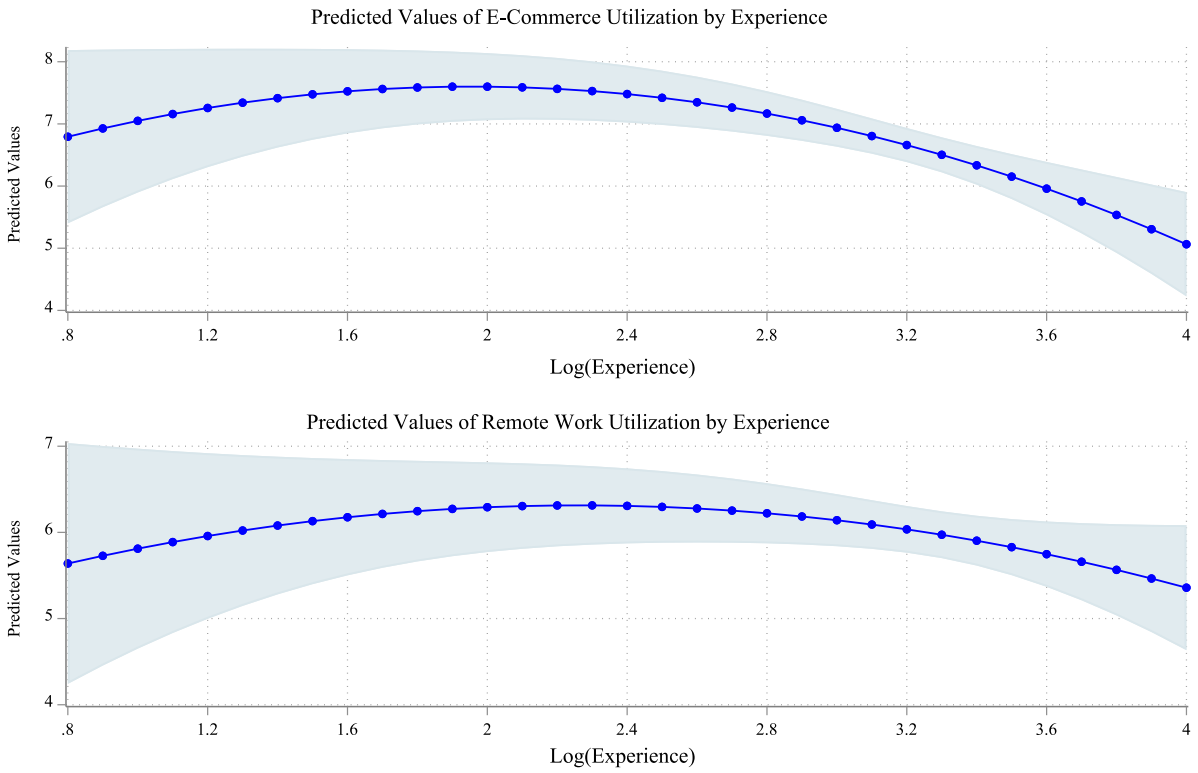

Fig. 2. Predicted values of digital technology utilization at different levels of experience.

commerce adoption is negative among female-led firms. Coupled with the results in Table 3, which indicated significantly less remote work adoption among female-led firms, this result provides robust support for the negative link between CEO gender and technology adoption. Overall, therefore, the analysis provides robust support for Hypothesis 1a.

The interaction between "female CEO" and "small size" is weakly significant in regressions 5 and 6 (at 10 % level), suggesting that female-led, small firms utilize e-commerce technologies less intensively. In other words, the *marginal effect* of small firm size on e-commerce utilization is negative among female-led firms. Overall, however, the evidence base for the negative association between CEO gender and technology utilization is not robust, as shown in Table 4. These results are in line with the risk-based explanation of technology adoption differences between female and male CEOs. In some technologies like e-commerce, risk aversion among female CEOs seems to affect technology adoption only in smaller, more financially-constrained firms. However, this explanation seems to be relevant only for explaining the relatively risky decision of adopting new technologies rather than the less risky decision of technology utilization.

6. Discussion and conclusion

COVID-19 has spawned an unprecedented level of digital transformation by encouraging e-commerce and remote work, thus upending the sluggish rate of technology adoption in the pre-pandemic period (Singh and Verma, 2020). These trends are expected to continue apace in the post-pandemic period, permanently altering the nature of work and reshaping the competitiveness and resilience of business enterprises. Digital technologies have enabled companies to streamline and transform their operational processes, rejuvenate growth through improved market access, and improve employee motivation and productivity (Kazekami, 2020; Ollo-López et al., 2020; Martin and MacDonnell, 2012). During the pandemic, digital technologies also helped in reducing the risk of viral contagion (Caselli et al., 2021), enabling companies to protect the safety and wellbeing of their workers and customers (Ollo-López et al., 2020).

The effects of rapid uptake in digital technologies are likely to be lasting, as digital technologies can enable businesses to build dynamic digital capabilities (Belitski et al., 2022; Teubner and Stockhinger, 2020) that offer a sustained, competitive edge over their competitors (Carillo et al., 2021). Enterprises with digital capabilities can successfully reconfigure their processes of value creation, delivery and capture to achieve greater agility, adaptiveness in the face of significant uncertainties (Chen et al., 2017). Digital technologies can also increase firm resilience by enhancing the readiness of enterprises to anticipate future adversities and devise appropriate responses (Khurana et al., 2022; Birhanu et al., 2022). This requires potentially risky decisions to take on new investment opportunities during a crisis, as opposed to retrenching or even exiting the market (Krammer, 2022).

Small and medium enterprises, however, tend to lag in adopting digital technologies because of their limited capabilities and resources, which can expose them to loss of competitiveness and resilience (OECD, 2021). Indeed, there is a growing concern that large enterprises with vast technological might could gobble up the market share of small businesses, just as Amazon's immense growth during the pandemic came at the expense of small, brick-and-mortar retail stores that were forced to close down. New digital technologies can thus turbocharge the growth of large corporations, in the process decimating SMEs, hollowing out local economies, and worsening income inequalities. At the same time, digital technologies provide an opportunity form SMEs to narrow their technology deficit, improve their productivity (Chen et al., 2017), and advance their competitiveness (Cenamor et al., 2019). SMEs that successfully responded to the pandemic by adopting digital technologies and modernizing their operations could thus improve their long-term competitiveness and resilience.

Although the pandemic has provided a great setting for understanding divergent enterprise responses to technology adoption, our understanding of technology uptake in SMEs has been up until now limited (OECD, 2021). This study looked into the role of top management attributes – gender and experience – on pandemic-era technology

Table 5
The interaction between firm size and CEO gender, and its effects on digital technology adoption and utilization.

	Digital technology adoption				Digital technology utilization			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	E-commerce (binary)	E-commerce (binary)	Remote work (binary)	Remote work (binary)	E-commerce (% sales)	E-commerce (% sales)	Remote work (% workforce)	Remote work (% workforce)
Female CEO x Small size	−0.109**	−0.109**	−0.004	−0.001	−1.122*	−1.126*	−0.116	0.048
	(0.047)	(0.048)	(0.049)	(0.048)	(0.643)	(0.646)	(0.551)	(0.559)
Female CEO	0.071**	0.052	−0.051	−0.062*	0.762	0.578	0.002	−0.169
	(0.034)	(0.035)	(0.034)	(0.034)	(0.494)	(0.496)	(0.411)	(0.421)
Small size	−0.189***	−0.204***	−0.726***	−0.727***	0.610	0.565	−2.416***	−2.382***
	(0.048)	(0.046)	(0.061)	(0.060)	(0.477)	(0.484)	(0.537)	(0.546)
Medium size	−0.043	−0.065*	−0.419***	−0.418***	0.598*	0.537	−1.903***	−1.860***
	(0.038)	(0.038)	(0.047)	(0.047)	(0.356)	(0.362)	(0.406)	(0.417)
Log(CEO Experience)		0.273***		0.156*		2.352**		1.446
		(0.093)		(0.090)		(1.104)		(1.049)
(Log(CEO Experience))^2		−0.063***		−0.045***		−0.604***		−0.321
		(0.018)		(0.017)		(0.216)		(0.200)
Business closure	0.003	0.003	0.002	0.002	0.022	0.026	0.095***	0.099***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.029)	(0.029)	(0.034)	(0.035)
Internet access (binary)	0.327***	0.323***	0.161***	0.168***	2.121***	2.174***	0.794***	0.902***
	(0.033)	(0.033)	(0.029)	(0.029)	(0.308)	(0.307)	(0.273)	(0.279)
New products/ services (binary)	0.261***	0.267***	0.184***	0.189***	1.570***	1.657***	1.170***	1.359***
	(0.036)	(0.036)	(0.034)	(0.034)	(0.456)	(0.452)	(0.429)	(0.436)
Quality certification (binary)	−0.027	−0.029	0.166***	0.168***	−0.764**	−0.781**	0.598*	0.623*
	(0.028)	(0.028)	(0.033)	(0.034)	(0.365)	(0.366)	(0.329)	(0.338)
R&D expend. (binary)	0.041	0.033	0.198***	0.190***	−0.017	−0.014	1.126**	1.080**
	(0.036)	(0.036)	(0.031)	(0.032)	(0.469)	(0.479)	(0.444)	(0.462)
ICT constraints	0.008	0.006	−0.000	0.001	−0.007	−0.020	−0.069	−0.078
	(0.008)	(0.008)	(0.007)	(0.008)	(0.090)	(0.093)	(0.085)	(0.088)
Log(Age)	−0.064***	−0.027	−0.001	0.040**	−0.472**	−0.063	−0.204	−0.083
	(0.016)	(0.019)	(0.018)	(0.019)	(0.205)	(0.226)	(0.175)	(0.191)
Exporting (binary)	−0.041	−0.049	0.072**	0.079**	0.907**	0.919**	1.194***	1.226***
	(0.033)	(0.033)	(0.031)	(0.031)	(0.410)	(0.417)	(0.367)	(0.378)
Foreign owned (binary)	−0.026	−0.034	0.333***	0.321***	1.573***	1.456***	1.994***	1.889***
	(0.036)	(0.035)	(0.034)	(0.035)	(0.528)	(0.535)	(0.505)	(0.515)
Public owned (binary)	−0.116	−0.135	−0.239*	−0.278**	−0.655	−0.951	−0.640	−0.593
	(0.111)	(0.111)	(0.136)	(0.133)	(1.031)	(1.054)	(1.056)	(1.060)
Constant	−1.042***	−1.293***	−0.727***	−0.999***	−1.341	−3.894**	−0.207	−1.880
	(0.162)	(0.211)	(0.235)	(0.327)	(1.089)	(1.644)	(1.195)	(1.650)
Observations	21,582	20,966	21,883	21,287	21,002	20,473	21,707	21,132
R-squared					0.162	0.165	0.176	0.176

Notes: Regressions 1–4 are based on the probit model, and regressions 5–8 are based on OLS. City-by-month and 2-digit level ISIC industry fixed effects are included but not reported. Standard errors in parentheses have been corrected for clustering within country-sector groups.

adoption and utilization among an international sample of small and medium enterprises. Building on diverse streams of research in Upper Echelon Theory, human capital and resource-based view theories (Marcati et al., 2008; Gómez and Vargas, 2012), and the behavioral perspective of innovation research (Strohmeyer et al., 2017; Roy and Sarkar, 2016; Assink, 2006), we elaborated how CEOs' gender and experience shape their risk-taking attitude and crisis responsiveness, thus affecting technology adoption decisions.

We tested our hypotheses using a rich dataset of 20,000 establishments across 42 countries, 80 % of which are small and medium enterprises with <100 workers. The results show that female CEOs were less likely to adopt remote work technologies; moreover, female CEOs leading smaller businesses (<20 workers) were less likely to adopt e-commerce. However, the results do not provide support for the hypothesis that female CEOs are less likely to utilize digital technologies more intensively. This suggests that female CEOs perform on par with male CEOs in utilizing existing technologies although they appear to be less likely to introduce new technologies during the pandemic. Moreover, the analysis reveals that CEO experience has an inverted U-shaped relationship with the adoption and utilization of e-commerce and remote work, indicating that managers with moderate levels of experience are more likely to adopt and utilize these technologies. Together, these results shed light on the role that individual CEOs can play in shaping technology adoption during the pandemic, influencing the journey of their respective enterprises towards digital transformation. As such, the results shed light on "how individual-level factors aggregate to collective level" outcomes in technology adoption (Barney and Felin, 2013, p. 145), shedding light on the micro-foundations of digital transformation in SMEs (Storbacka et al., 2016).

Like all other research work, this study has a number of caveats that can be improved in future research. First, the study uses a uniquely international dataset with a large sample and adopts a specification that includes a large number of control variables and hundreds of city-by-month fixed effects. While these measures can significantly reduce omitted variable bias risk, the cross-sectional research design cannot guarantee causality. The evidence presented here should thus be seen as

associational. Moreover, our analysis did not directly control for CEO age as our dataset did not include such a measure. Since age and experience are highly correlated, isolating the effect of one from another is always challenging. Future research can further refine our results by testing the relationship between CEO age and experience and their effects on technology adoption.

Second, our study explains adoption and utilization without directly assessing their relevance for enterprise performance. The performance effects of digital technologies like remote work are multifaceted and potentially contingent on factors such as task attributes (such as degree of routinization), incentive design, monitoring protocol and employee loyalty or opportunism (Ollo-López et al., 2020). The quality of execution, such as the development and coordination of new work routines, could also shape the effectiveness of remote work strategies. Moreover, our measures of technology adoption capture both new investments and decisions to expand existing digital capabilities. Future research can relate how the adoption of digital technologies influenced performance using metrics such as survival and duration of closure during the pandemic. It is also vital to identify complementary resources, from employee skillsets to environmental attributes, that enable digital technologies to improve enterprise competitiveness and performance. Further, it is crucial to understand if technology adoption during the pandemic represented merely a transitive shift towards digital technologies or a more sustained process of digital transformation that fundamentally redefined business models and value networks.

Another important area of future research is the potential unintended side effects of digital technologies. The adoption of remote work and e-commerce technologies has improved the welfare of customers and employees, respectively, by providing them with greater flexibility, autonomy and choice. At the same time, these technologies could give rise to diverse unanticipated effects, especially during the pandemic when their adoption was sudden, radical and, in many ways, compulsory (Carillo et al., 2021). For example, remote work during the pandemic has been associated with increased work-life conflict that had a particularly severe effect on women managers and entrepreneurs (Birhanu et al., 2022). Future research can shed light on the potential adverse effects of digital transformation on various stakeholders and identify potential mitigating factors.

Data availability

Data will be made available on request.

Appendix A. Appendix

Table A1
The number of observations per country, and average values of the outcome variables.

Country	# Obs	E-commerce (binary)	Remote work (binary)	E-commerce (% sales)	Remote work (% workforce)
1. Albania	334	0.16	0.13	2.46	1.35
2. Armenia	337	0.39	0.39	7.02	1.08
3. Belarus	529	0.26	0.31	4.86	2.99
4. Bosnia & Herzeg.	234	0.14	0.30	1.01	0.95
5. Bulgaria	1014	0.10	0.15	2.07	1.23
6. Chad	101	0.06	0.01	0.26	0.63
7. Croatia	669	0.14	0.33	2.05	1.61
8. Cyprus	339	0.26	0.39	3.14	3.29
9. Czech Republic	794	0.25	0.48	6.31	8.39
10. El Salvador	803	0.44	0.49	11.95	7.87
11. Estonia	558	0.25	0.40	5.04	4.06
12. Georgia	981	0.23	0.45	5.46	5.80
13. Greece	1071	0.23	0.43	4.37	3.69
14. Guatemala	386	0.43	0.55	11.59	13.64
15. Guinea	103	0.20	0.15	6.63	5.91
16. Honduras	322	0.53	0.54	13.03	14.11
17. Hungary	1262	0.12	0.27	3.32	1.56
18. Italy	840	0.20	0.50	4.11	8.23
19. Jordan	942	0.48	0.26	0.81	3.74
20. Kazakhstan	795	0.31	0.45	6.14	7.31
21. Latvia	497	0.34	0.29	28.20	17.96
22. Lebanon	364		0.12	2.19	4.15
23. Lithuania	427	0.28	0.50	6.73	6.56
24. Malta	386	0.26	0.52	7.98	3.85
25. Moldova	564	0.32	0.39	5.68	5.14
26. Mongolia	530	0.35	0.52	7.47	15.80
27. Montenegro	135	0.21	0.16	3.60	2.62
28. Morocco	1489	0.39	0.27	12.06	4.81
29. Mozambique	219	0.13	0.15	2.16	
30. Nicaragua	373	0.41	0.41	12.65	7.56
31. Niger	65	0.08	0.15	1.62	2.19
32. North Macedonia	291	0.22	0.18	3.95	2.29
33. Poland	1965	0.27	0.34	10.47	5.84
34. Portugal	1513	0.16	0.33	2.97	4.94
35. Romania	973	0.17	0.28	3.54	3.28
36. Russia	1139	0.54	0.52	18.81	13.07
37. Serbia	310	0.23	0.26	5.39	5.62
38. Slovakia	626	0.20	0.41	7.01	6.45
39. Slovenia	500	0.23	0.40	3.36	5.73
40. Togo	49	0.12	0.14	3.18	0.77
41. Zambia	1056	0.30	0.32	9.42	8.44
42. Zimbabwe	536	0.23	0.23	5.23	7.13
Mean	620	0.26	0.33	6.32	5.65
Minimum	0	0.06	0.01	0.26	0.63
Maximum	1965	0.54	0.55	28.20	17.96

Table A2
The number of observations per industry, and average values of the outcome variables.

ISIC code	Industry name	# Obs	*E*-commerce (binary)	Remote work (binary)	E-commerce (% sales)	Remote work (% workforce)
15	Manufacture of food products and beverages	3473	0.25	0.32	4.84	3.92
16	Manufacture of tobacco products	23	0.30	0.43	6.67	2.32
17	Manufacture of textiles	341	0.30	0.38	5.75	3.62
18	Manufacture of wearing apparel; dressing and dyeing of fur	1376	0.31	0.31	9.45	5.22
19	Tanning and dressing of leather products	186	0.25	0.22	5.57	4.13
20	Manufacture of wood and of products of wood and cork	453	0.15	0.33	4.93	5.45
21	Manufacture of paper and paper products	189	0.25	0.41	7.46	3.23
22	Publishing, printing and reproduction of recorded media	517	0.39	0.44	11.98	11.64
23	Manufacture of coke, refined petroleum products and nuclear fuel	24	0.29	0.29	3.43	10.09
24	Manufacture of chemicals and chemical products	426	0.34	0.52	6.10	7.07
25	Manufacture of rubber and plastics products	703	0.24	0.42	7.21	5.92
26	Manufacture of other non-metallic mineral products	693	0.26	0.35	6.26	5.60
27	Manufacture of basic metals	175	0.19	0.39	1.82	5.03
28	Manufacture of fabricated metal products	1851	0.15	0.35	3.79	4.34
29	Manufacture of machinery and equipment	1453	0.22	0.42	4.32	5.22
30	Manufacture of office, accounting and computing machinery	14	0.31	0.50	11.54	7.21
31	Manufacture of electrical machinery and apparatus	254	0.22	0.48	5.33	6.62
32	Manufacture of radio, television and communication equipment	48	0.33	0.63	7.11	8.63
33	Manufacture of medical, precision and optical instruments	126	0.23	0.44	4.48	7.74
34	Manufacture of motor vehicles, trailers and semi-trailers	160	0.19	0.55	5.61	6.90
35	Manufacture of other transport equipment	80	0.14	0.39	3.29	3.13
36	Manufacture of furniture; manufacturing	806	0.27	0.31	7.35	4.58
37	Recycling	93	0.21	0.31	3.31	3.96
45	Construction	2025	0.20	0.32	4.53	6.99
50	Sale, maintenance and repair of motor vehicles and motorcycles	1012	0.22	0.27	5.68	3.75
51	Wholesale trade and commission trade	1986	0.36	0.45	8.88	8.84
52	Retail trade (other); repair of personal and household goods	4654	0.36	0.31	8.35	4.66
55	Hotels and restaurants	1517	0.25	0.23	8.18	4.09
60	Land transport; transport via pipelines	692	0.20	0.36	6.18	6.07
61	Water transport	24	0.43	0.54	9.78	10.70
62	Air transport	15	0.67	0.80	35.00	11.67
63	Supporting and auxiliary transport activities	296	0.24	0.59	11.11	12.84
64	Post and telecommunications	107	0.55	0.62	17.45	23.26
72	Computer and related activities	394	0.46	0.70	22.91	30.01
Mean		*(26,186)*	*0.27*	*0.36*	*6.93*	*5.91*
Minimum		*14*	*0.14*	*0.22*	*1.82*	*2.32*
Maximum		*4654*	*0.67*	*0.80*	*35.00*	*30.01*

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