DIGITAL DIVIDE DECODED: CAN E-COMMERCE AND REMOTE WORKFORCE ENHANCE ENTERPRISE RESILIENCE IN THE COVID-19 ERA?*

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We examine the impact of COVID-19 on the performance of 12,000 firms in 32 countries and find that the majority of firms experienced permanent or temporary closures, decreased sales and working hours, reduced production capacity, and worker layoffs. However, the impact was heterogeneous across countries and industries. After controlling for firm characteristics, macroeconomic conditions, and pandemic prevalence, firms that have access to digital infrastructure performed better than those that do not. The key channel is an enhanced capacity to adopt e-commerce business models and employ larger share of the remote workforce, which boosts resilience when social distancing measures are mandated.

Keywords: Digital Infrastructure; Technology Transformation; Working From Home; Labor Productivity
JEL Classification: M11; L25; H12

1. INTRODUCTION

The COVID-19 pandemic upended lives and economies. Analysts predict that the global economy may be facing the deepest recession since the end of World War II (World Bank, 2020a). At the same time, this crisis has highlighted the central role of

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digital connectivity in keeping our societies functioning, as ‘online everything’ quickly became our new way of life (Katz, 2020). The sweeping operating-model transformation prompted by the coronavirus is raising existential challenges for traditional business models and the workforce of those models (Iansiti and Richards, 2020). Firms that have invested in the digital transition path will do well while those that did not will struggle, creating a new Digital Divide.

Despite the wide spread of information and communication technology (ICT) or digital technology, it is not simple to clearly define the concept of the digital economy. For instance, according to the OECD (2020): “The Digital Economy incorporates all economic activity reliant on, or significantly enhanced by the use of digital inputs, including digital technologies, digital infrastructure, digital services and data”. Buhkt and Heeks (2017) refer to the digital economy as all businesses and services whose operating models are mainly based on buying, selling, or providing digital products and services, or supporting devices and infrastructure. The digital economy is expected to account for about 22.5% of global GDP in this decade (Knickrehm et al., 2016).

ICT adoption can have a significant impact on development in many different ways. First, ICT boosts economic growth by improving productivity, fostering new business models and opportunities, and promoting innovation and entrepreneurship. Second, digital technologies can create new job opportunities and reduce unemployment rates, especially in sectors that rely heavily on ICT such e-commerce and telecommunication. Third, ICT enhances the quality of education by providing access to digital learning resources, enabling online education and improving the effectiveness of teaching and learning processes. Fourth, digital technologies can improve healthcare delivery by facilitating remote consultations, electronic health records, and telemedicine. Fifth, the adoption of ICT can improve governance by enhancing transparency, accountability, and citizen participation. This leads to better public services, increased citizen engagement, and more responsive government. Finally, ICT can help promote social inclusion by providing access to information and services to marginalized communities, thus empowering them and reducing inequality.

Given the crucial role of the digital-economy development, there is an important related concept, namely the Digital Divide. This is defined by the OECD as the disparity between different individuals, households, communities, businesses, and geographical regions in terms of both opportunities to access ICT and the use of the internet in various activities.[1] Simply put, it is the gap between those who actually have access to ICT and are able to use it effectively and those who do not. Recent years witnessed many national and international efforts to narrow the digital gap, which is both a consequence and cause of inequality (United Nations, 2020). However, previous research contains only the quantitative analysis of the Digital Divide. For example, Corrocher and Ordanini (2002) measure the digital divide for ten developed countries during the period 2000-2001 by performing principal components analysis on six factors of digitalization

[1] Available at https://stats.oecd.org/glossary/detail.asp?ID=4719

but could not explain the cross-country differences. Meanwhile, Rückert et al. (2020) confirm a growing digital divide across firms in the EU and the U.S. While firms that are digitally inactive are falling behind, digitally active firms are forging ahead. Market concentration is growing, with higher mark-ups evident in sectors where digital technology is widely diffused (Calligaris et al., 2018).

The concept of Digital Divide and its role have been previously recognized in the existing literature. Ayanso et al. (2010) provides an analysis on the gap between ICT leaders and followers at both global and regional levels. The authors argue that the digital divide is not just a gap between those who have access to technology and those who do not, but also a gap between ICT leaders and followers. Reddick et al. (2012) argue that the digital divide not only exists in terms of access to technology but also in terms of access to information and services online. Armenta et al. (2012) opine that the digital divide is not only a matter of access to technology, but also a matter of how technology is used to promote sustainable development and community participation. In the same vein, Pick et al. (2021) found that the digital divide is not just a matter of access to technology but is also linked to socio-economic factors. They also found that the digital divide is more pronounced in rural and low-income areas. Meanwhile, Heeks (2022) aims to go beyond the traditional concept of the digital divide and propose a new conceptualization of digital inequality in the Global South. The author argues that the traditional concept of the digital divide, which focuses on access to technology, is inadequate in understanding the complex ways in which technology can impact people's lives. The author proposes a new concept of "adverse digital incorporation," which captures the negative impact of technology on people's lives, such as job displacement, loss of privacy, and social exclusion.

Ayanso et al. (2014) provide an assessment of the global and regional digital divide and the role of ICT development in bridging this divide. The authors argue that despite the significant growth in ICT development in recent years, the digital divide still exists, particularly in developing countries. The paper presents a review of literature on the digital divide and identifies various factors that contribute to the divide, including infrastructure, affordability, and literacy. Sein and Furuholt (2012) explore the role of intermediaries in bridging the digital divide, particularly in developing countries. The authors argue that intermediaries, defined as individuals or organizations that act as intermediaries between technology producers and users, play a critical role in facilitating technology adoption and diffusion.

To add to the above literature, this paper sheds light on the significance of the Digital Divide in the context of the COVID-19 pandemic. Prior to the pandemic, the adoption of IT practices was optional for many businesses and countries. As a result, the full impact of the Digital Divide was not entirely clear. However, the outbreak of COVID-19 and subsequent social distancing and lockdown measures have made the adoption of IT practices essential for businesses to survive. This has created a natural experiment to assess the impact of IT on development, and the effects of Digital Divide across various countries and business entities. By analysing these matters, this paper offers valuable insights into the impacts of Digital Divide, particularly in times of crisis, and highlights the importance of IT adoption for development. Overall, we seek to demonstrate the relevance and importance of the Digital Divide in today's world, and provide a new perspective on its potential impact by answering the following questions:

(1) What is the impact of the digital divide during the COVID-19 pandemic, and how does it vary across countries and industries?

(2) How does digital access affect the potential of e-commerce and remote workforce management and overall firms' resilience?

The contribution of our study to the existing literature is three-fold. First, we devise a tractable way to measure the effect of the digital divide during the pandemic based on website ownership and social media platform usage. Second, we provide insights into the heterogeneity of the digital effect across many countries and industries. Third, we empirically test whether digital access enhances the potential of e-commerce and remote workforce. Specifically, in order to explain diverse firm performance during the pandemic, we empirically assess the role of access to digital infrastructure in the resilience of businesses. After taking into account firm characteristics, macroeconomic conditions, and pandemic prevalence, we found that firms that have access to digital infrastructure performed significantly better than those that do not by taking advantage of e-commerce opportunities and adopting improved workforce management practices.

The remainder of the paper is organised as follows. Section 2 reviews three related strands of literature on the role of the pandemic in accelerating digital transformation. Section 3 discusses the various models used in our empirical analysis. Section 4 describes the data and reports some preliminary analyses. Section 5 reports and discusses the main empirical results on the impact of access to digital infrastructure on firms' resilience during the COVID-19 pandemic. Finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

2.1. The Impact of the COVID-19 Pandemic on Business Operations

Much more than a health crisis, COVID-19 affects all aspects of our life, economy, and society. Production disruptions first emerged in Asia but spread quickly to supply chains around the world. Nevertheless, the impacts of the COVID-19 shock are asymmetric across industries (Bloom et al., 2021). Most businesses, regardless of size, faced serious challenges. This is especially true for industries that involve social contacts such as aviation, tourism, and hospitality industries. Many businesses suffered business income losses and even insolvency and laid-off workers. Furthermore, the effects of the COVID-19 outbreak vary across firms (Apedo-Amah et al., 2020). Staying in business is especially difficult for small and medium-sized enterprises (SMEs). Due to social distancing restrictions, many workers are unable to perform their jobs. This has a severe impact on the incomes of workers, especially informal and temporary workers. Consumers were unable or reluctant to purchase desired goods and services. In the uncertain and worrisome COVID-19 environment, businesses are likely to delay investing, buying goods, and hiring workers.

E-commerce is probably the most notable example of an industry that thrived during the pandemic. According to a recent UNCTAD report, e-commerce saw a tangible rise in its share of global retail sales, from 16% to 19% in 2020.[2] The success of e-commerce businesses does not stem from hiring hundreds of workers nor investing heavily in brick-and-mortar stores. Instead, e-commerce businesses invest in developing and managing online websites. Online shopping giants such as Amazon, Alibaba, Shopify, and Etsy have grown rapidly during COVID-19. COVID-19 is a major catalyst that amplified the role of e-commerce in the retail sector.

The spread of COVID-19 and containment measures adversely affect productivity (Bartik et al. 2020; di Mauro and Syverson, 2020) due to increases in intermediate costs (Bloom et al., 2021). The allocation of resources within countries as well as across sectors and firms is limited due to mobility restrictions and higher transaction costs (Apedo-Amah et al., 2020). Consequently, allocative efficiency and aggregate productivity growth declines. Bloom et al. (2021) estimated that total factor productivity in the UK private sector dropped by almost 5% during the fourth quarter of 2020 and a 1% in the medium term. Further, the effects of the pandemic appear to be pronounced among firms in low-productivity sectors. On the other hand, induced innovation may mitigate the productivity-decelerating effects of the crisis (di Mauro and Syverson, 2020). The disruption might put pressure on firms to expand their use of digital technologies or platforms to develop and implement new business models, resulting in higher productivity growth (Apedo-Amah et al., 2020).

Apedo-Amah et al. (2020) provide a comprehensive analysis of the short-term influence of the COVID-19 pandemic on businesses around the world. Based on a novel data set of more than 100,000 businesses in 51 countries worldwide, the study documented a pronounced impact of the pandemic, especially persistent negative effects on sales. Leave of absence and reduction in working hours accounted for most of the employment adjustment while employee layoffs accounted for a small share. Financial constraints were a greater problem for smaller firms. Additionally, digital solutions were a critical tool for firms to cope with the pandemic shock. Firms that suffered a larger decline in sales faced greater uncertainty about the future, evident in job losses.

2.2. Working from Home and Productivity

Given the high transmission risk of COVID-19, instead of directly operating in

[2] Available at https://unctad.org/system/files/official-document/tn_unctad_ict4d18_en.pdf

offices, many businesses switched to working remotely or work from home (WFH). Interestingly, COVID-19 re-directed technical transformation in ways that enhanced remote interactivity (Bloom et al., 2021). For instance, the number of new U.S. patent applications that improved WFH technologies increased by more than twice from January to September 2020 (Barrero et al., 2021). Useful technologies that facilitate working remotely include chat, job assignment, timekeeping, and business management software.

Remote teamwork is an appropriate work model for the digital environment. This model is being deployed by more and more companies, especially those specializing in technology. The application of technology to remote work reduces costs, increases profits, and enhances customer satisfaction. Barrero et al. (2021) attribute the new working arrangements to a boost in labour productivity of 5% relative to the pre-pandemic situation. Along the same vein, WFH is found to raise productivity by 7.6% in a natural experiment of call center workers in the call centres of a Fortune 500 online retailer during 2018-2020 (Emanuel and Harrington, 2021). Similarly, randomized control trials show that WFH improves the total factor productivity of Ctrip, China's largest travel agency, by between 20% to 30% (Bloom et al., 2015). Giving employees some flexibility over time and place of work improves their productivity in a randomized experiment at a large Italian firm (Angelici and Profeta, 2024).

However, the performance and productivity of the WFH model depend on each person's responsibility, professional style, and working style. Before the COVID-19 pandemic, WFH was often perceived as a form of shirking (Barrero et al., 2021). A pre-COVID analysis reveals that productivity declines by 12% for workers who selected WFH (Emanuel and Harrington, 2021). At the same time, many workers value social interactions at work and opted to return to the office even though they were allowed to WFH (Bloom et al., 2015). Additionally, many factors such as technology, internet connection, data connection, and the specific nature of work have a significant impact on the effectiveness of the WFH model. Therefore, it is not easy to effectively organize and manage individuals, teams, and entire businesses remotely. Research reveals that managers tend to be more concerned about remote work for collaborative work (Beham et al., 2015; Juhász et al., 2020). Conscious planning, combined with professional work attitudes from WFH employees, is essential to productive collaboration.

In summary, the spread of COVID-19 has forced a large share of the workforce to work remotely, although the levels of remote work vary considerably across industries (Bartik et al., 2020). Despite its potential benefits, WFH also entails significant challenges to businesses since they need to understand their teams well to ensure that they function well. One example is identifying the employees who are suitable for WFH and monitoring the work of WFH employees.

2.3. A Pandemic-Induced Deluge of E-Commerce Opportunities

E-commerce (electronic commerce), the buying or selling goods and services over the internet, first emerged in the 1960s. At a broader level, e-commerce refers to transactions, purchases and sales, payments, orders, advertisements, and even deliveries of products and services using electronic means such as EDI (electronic data interchange), electronic mail, fax transmissions, radio, television, and computer networks or the internet (Wong, 2013). The major advantage of e-commerce is that it automates business activities and allows the provision of personalized goods and services any time anywhere (Clarke, 2001). Some industries that use e-commerce extensively include mobile commerce, electronic money transfer, supply chain management, internet marketing, online transactions, EDI, inventory management systems (Rahman, 2014). E-commerce helps businesses promote their brand and enhance their presence in the market by providing a less costly and more efficient supply chain. As a result, e-commerce adoption has a positive effect on product prices and supply process quality (Baršauskas et al., 2008).

Even before the pandemic, consumers had been more demanding about choosing products, sharing personal information, and deciding how they shop. In light of unprecedented consumer empowerment, creating and managing a great customer experience is the key to business success (Lemon and Verhoef, 2016). Online shopping has helped businesses collect and analyze user data, eliminate human error from their service, and optimize the customer experience (Ordanini and Rubera, 2010). The number of digital buyers has been increasing steadily, from 1.3 billion in 2014 to 2.1 billion in 2021. E-commerce also opens up many new opportunities and markets for SMEs and startups. In recent years, many businesses in the developing world have digitally transformed themselves, making breakthroughs in production methods and goods quality. SMEs generally have limited access to market information about consumer behavior, alternative suppliers, and potential business partners (Madrid-Guijarro et al., 2009). Adopting e-commerce renders market information cheaper, faster, and more accessible. As a result, many businesses in developing countries are able to reduce their transaction costs, which facilitates their participation in global supply chains (Hempel and Kwong, 2001; Molla and Licker, 2005).

The COVID-19 pandemic accelerates digital transformation worldwide. Online transactions spiked as global consumers became more familiar with online shopping processes. Countries hit hardest by the pandemic experienced strong demand for e-commerce as a result of lockdowns and community quarantines. Realizing the potential of e-commerce, many businesses moved from brick-and-mortar retail stores to online stores in order to stay in business. The global e-commerce industry is likely to continue to grow rapidly in the coming years (Evans, 2021).

3. METHODOLOGY AND DATA

In this study, we use ownership of a website or social media page as a proxy for the capability to do business online. Without access to online infrastructure such as a website, it is difficult for a firm to shift their activities and workforce online.[3] The functional form of the econometric models depends on the nature of the dependent variables. Throughout this paper, we examine three types of outcomes: (i) continuous variables; (ii) binary variables; and (iii) ordered-categorical variables. In the following, we set out our models corresponding to each type of variable. For tractability, model descriptions are simplified with different notations only for the elements that fundamentally distinguish the models.

3.1. Linear Regression Model

We use the following specification to analyze firms' outcomes that are measured by continuous variables, for example, the number of weeks closed due to COVID-19 or the share of workers laid-off. The model has the form

$$y_{1i} = ay_{2i} + X_i'b + \varepsilon_i, \tag{1}$$

in which y_{1i} denotes the outcome. y_{2i} denotes the main explanatory variable of interest, a binary variable indicating whether a firm owns a website or not. $X_i = \{x_{ki}\}(k = 1, \dots, K)$ is a vector of K control variables capturing pre-COVID-19 firm characteristics and determinants of firm performance. These are well established in the literature and defined in Table 2 of the next section.[4] ε_i denotes an error term with a standard normal distribution. The estimated coefficients of the parameters ω and $\beta = \{\beta_k\}$, respectively, capture the effects of our variable of interest, website ownership, and of the control variables, on firm outcome y_{1i}.

3.2. Probit Model

We use this model to analyze binary outcomes, such as whether a firm closed temporarily or not during the pandemic. The unobservable (latent) underlying data generating process is

$$y_{1i}^* = ay_{2i} + X_i'b + \varepsilon_i, \tag{2}$$

[3] Subsequently, we report in Section 5 that website ownership pre-2020 indeed strongly correlates with the capability of adopting an online business model, providing delivery services, and managing a remote workforce.

[4] These include physical and human capital endowments, growth rates of annual sales, size, age, ownership structure, and the level of competition. We also control for industry effects with a dummy variable indicating whether a firm operates in the manufacturing sector. At the macro level, we also control for national economic policy changes as measured by the Government Economic Support Index of Hale et al. (2020) as well as the changes in the COVID-19 situation as measured by the growth rate of new cases per million people (Dong et al., 2020).

in which y_{1i}^{*} denotes a continuous latent variable capturing the propensity of firm i exhibiting a particular outcome. X_i and ε_i are defined as in model (1). Though y_{1i}^{*} is unobservable, the propensity of an outcome is related to the observed firm performance, as captured by a binary variable y_{1i}. The relationship between y_{1i} and y_{1i}^{*} can be expressed via a link function, denoted as $g(y_{1i}^{*})$:

$$y_{1i} = g(y_{1i}^{*}) = \begin{cases} 0 \; if \; y_{1i}^{*} \leq 0 \\ 1 \; if \; y_{1i}^{*} > 0 \end{cases}. \tag{3}$$

For estimation, (3) can be rewritten as

$$Pr(y_{1i} = 1) = 1 - \Phi(-\omega y_{2i} - X_i'\beta), \tag{4}$$

where Φ denotes the standard cumulative normal distribution function. The parameters ω and β capture the effects of website ownership and the control variables on the log-odds of the outcome. In our empirical analyses, we opt for transforming these coefficients into marginal effects as:

$$\frac{\delta Pr(y_{1i} = 1)}{\delta y_{2i}} = Pr(y_{1i} = 1 | y_{2i} = 1) - Pr(y_{1i} = 1 | y_{2i} = 0),$$

$$\frac{\delta Pr(y_{1i} = 1)}{\delta X} = [\Phi(-\omega y_{2i} - X_i'\beta)]\beta. \tag{5}$$

These are computed as averages across all firms, i.e., average marginal effects (AME), and can be interpreted as the effects on the probability of the outcome of a unit change in X_i' and in y_{2i} - i.e., going from "no website" to "have website".

3.3. Ordered Probit Model

The ordered probit (hereafter, oprobit) model generalizes its probit variation by dividing the continuum of outcome possibilities into a finite set of ranges, each corresponding to one possible outcome captured by firms' ordered categorical responses. As discussed in the next section, an example of the ordered categorical y_{1i} are the answers of firms to the question *"Is the firm currently open (1), temporarily closed (2) or permanently closed (3)?"*. It can be seen that there is a natural order of preference for these answers, with being "open" given by the least severely affected firms and being "permanently closed" given by the most severely affected firms. In our sample, all other variables similarly relate to choices of "Decreased", "Remain the same" or "Increased". Examples include production capacity or the number of a firm's work hours during the pandemic. In summary, there are always three alternative choices for each ordered categorical variable.

The underlying data generating process of oprobit is essentially the same as that of the probit model [Equation (2)]. The only difference is that the latent left-hand side variable y_{1i}^* now has three distinct values, rather than two. The link function in this case is

$$y_{1i} = g(y_{1i}^*) = \begin{cases} O_1 \; if \; c_0 \; \le \; y_{1i}^* \le c_1 \\ O_2 \; if \; c_1 \; \le \; y_{1i}^* \le c_2, \\ O_3 \; if \; c_2 \; \le \; y_{1i}^* \le c_3 \end{cases} \tag{6}$$

in which the ascending sequence of thresholds c_0, c_1, c_2, c_3 define the latent regions into which y_{1i}^* might fall, whereby $c_0 = -\infty$ and $c_3 = \infty$ and c_1, c_2 are parameters for estimation (Roodman, 2011). To estimate (5) we can rewrite it more compactly as:

$$Pr(y_{1i} = O_j) = \Phi(\mathrm{c_j} - \omega y_{2i} - X_i'\beta) - \Phi(\mathrm{c_{j-1}} - \omega y_{2i} - X_i'\beta), \tag{7}$$

where O_j denotes the j-th outcome ($j = 1,2,3$). The coefficients ω and β capture the effect of website ownership and control variables on the ordered log-odds of outcome j against the log-odds of other two outcomes, *ceteris paribus*. The corresponding marginal effects are

$$\frac{\delta Pr(y_{1i} \; = \; j)}{\delta y_{2i}} = \; Pr(y_{1i} = j|y_{2i} = 1) - Pr(y_{1i} = j|y_{2i} = 0),$$

$$\frac{\delta Pr(y_{1i} \; = \; j)}{\delta X} = [\Phi(\mathrm{c_j} - \omega y_{2i} - X_i'\beta) - \Phi(\mathrm{c_{j-1}} - \omega y_{2i} - X_i'\beta)]\beta. \tag{8}$$

Similar to the probit specification (5), here we compute the AMEs, which capture the effects on the probability of outcome j of a unit change in X_i and website ownership, averaged across all firms.

3.4. Addressing Endogeneity

A potential source of bias to a causal inference of the impact of website ownership is an endogeneity issue that arises from either (1) joint determination of such ownership and firm performance by unobserved firm characteristics or (2) omitted variables. For example, a firm that owns a website may also be more likely to adopt innovative technology that helps mitigate the impact of the pandemic. To address this concern, we instrument website ownership with a variable exogenous to the firm's choice, namely the number of power shortages the firm experienced during a typical month prior to the crisis. A reliable power supply is indispensable for taking advantage of e-commerce platforms such as websites or social media pages and ICT research and development, especially in developing countries (Li and Vo, 2021).

Table 1. Regression Models

Outcome variable type (1)	Model type (2)	Link function (3)	Specification: Baseline (4)	Specification: IV (5)
				First stage: $Pr(y_{2i}=1)=1-\Phi(-\gamma z_i - X_i'\delta)$
Binary	Probit	$y_{1i}=g(y_{1i}^*)=\begin{cases}0\ if\ y_{1i}^*\leq 0\\ 1\ if\ y_{1i}^*>0\end{cases}$	$Pr(y_{1i}=1)=1-\Phi(-\omega y_{2i}-X_i'\beta)$	Second stage: $Pr(y_{1i}=1)=1-\Phi(-\omega\hat{y}_{2i}-X_i'\beta)$
Ordered categorical	Ordered probit (oprobit)	$y_{1i}=g(y_{1i}^*)$ $=\begin{cases}O_1\ if -\infty< y_{1i}^*\leq c_1\\ O_2\ if\ c_1\leq y_{1i}^*\leq c_2\\ O_3\ if\ c_2\leq y_{1i}^*<\infty\end{cases}$	$Pr(y_{1i}=O_j)=\Phi(c_j-\omega y_{2i}-X_i'\beta)-\Phi(c_{j-1}-\omega y_{2i}-X_i'\beta)$ $(j=1,2,3)$	Second stage: $Pr(y_{1i}=O_j)=\Phi(c_{j-1}-\omega\hat{y}_{2i}-X_i'\beta)-\Phi(c_j-\omega\hat{y}_{2i}-X_i'\beta)$ $(j=1,2,3)$
Continuous	Linear	None	$y_{1i}=\omega y_{2i}+X_i'\beta+\varepsilon_i$	Second stage: $y_{1i}=\omega\hat{y}_{2i}+X_i'\beta+\varepsilon_i$

Notes: This table specifies the econometric models used throughout this paper to estimate the effects on outcome variables of different forms.

1. In all specifications:

- For each firm i, y_{1i} is the observed outcome variable, $\boldsymbol{X}_i$ denotes a vector of exogenous explanatory variables (definitions provided in Table 2 and the text) of which effects are captured by the vector of coefficients $\boldsymbol{\beta}$, and ε_i is a structural error term.

- All error terms are assumed to be independent and identically distributed normal for all i.

2. For probit and ordered probit models, y_{1i}^* is the latent propensity of observing the outcome and Φ denotes the standard cumulative normal distribution function. For the latter, O_j indicates the j-th outcome and c_j denotes the upper latent threshold corresponding to outcome j.

3. Instrumental-variable (IV) specifications [Column (5)]: y_{2i} denotes the endogenous dependent variable and $\hat{y}_{2i}$ its predicted value, z_i denotes the instrumental variable, u_i is the error term of the reduced-form equation (first stage) and ω is the main parameter of interest.

This instrumental variable reasonably satisfies the validity criterion and the exclusion restriction. While a high number of power shortages pre-COVID-19 reduces the probability of website ownership (as will be shown in our analyses), there is no direct link between it and firm performance during COVID-19, controlling for observed firm characteristics. To produce instrumental-variable (IV) estimates, we implement the conventional two-stage least square procedure for model (1), the IV-probit specification for model (2) (Rivers and Vuong, 1988), and a mixed-process IV-oprobit model (Roodman, 2011; Chesher and Smolinski, 2012).[5] Note that since y_{2i} is binary, the first stage of these IV regressions is itself a probit regression. Table 1 provides a summary of all model specifications described in this section.

3.5. Mechanisms of Website Ownership Effect

As discussed in Section 1, e-commerce and remote workforce are important determinants of firms' resilience since they facilitate stronger sales and production and mitigate the adverse impact on the labor force. Firms that can quickly (i) adopt and/or improve their online business model, (ii) invest in delivery service improvement, and (iii) increase the productivity of their remote workforce are more likely to overcome the pandemic. Digital options are not available to all firms in the pre-crisis period, and the digitalization decision depends crucially on the availability of digital infrastructure to firms. Therefore, we investigate the extent to which website ownership, an indicator of digital infrastructure, affects firms' choices in adopting online business practices. For this purpose, we extend our study with IV estimates of regression models similar to those described above, using the same instrument as previously. Online business practices are the dependent variable and website ownership is the independent variable of interest.

4. DATA DESCRIPTION

Our main data source is the firm-level World Bank Enterprise Surveys (WBES).[6] A primary advantage of the WBES is the comparability of a wide range of variables across a large number of countries. For discussions of other advantages, see Rodriguez-Meza (2020). We are interested in surveys conducted in two broadly defined data periods, entitled pre-2020 and 2020. The former corresponds to the latest pre-COVID-19 data available, from 2016 to 2019, that shed light on a broad range of business environment topics, including access to finance, corruption, infrastructure, crime, competition, and

[5] All IV estimates are computed with maximum likelihood approaches implemented via the Stata package "cmp" (Roodman, 2011).

[6] Available at https://microdata.worldbank.org/

firm-performance measures (World Bank, 2020c). The Enterprise Analysis unit collected information on exactly the same samples of firms surveyed in the pre-2020 period, in an effort to gain insights on the various firm-level impacts of the COVID-19 pandemic (World Bank, 2020b).[7] We use the first round of this follow-up survey, which covers the greatest number of countries and provides information on the immediate impact of the pandemic shock. At the time of our writing, the second round was only completed in a smaller number of economies, with virtually no data from African countries, while the third round is largely in the planning stages.

Importantly, the 2020 follow-up data can be merged with the baseline pre-2020 data with a unique firm identifier. Furthermore, to control for macro factors that affect firm performance during the survey period, such as government support and the severity of the pandemic, we collect data on the Economic Support Index from the University of Oxford (Hale et al., 2020) and the growth rate of new cases from John Hopkins University (Dong et al., 2020), respectively. These variables are recorded on a daily frequency, and thus can be matched with WBES data using the dates of the firm-specific interviews. Our merged cross-sectional sample consists of 12,990 unique firms interviewed between 5th May and 30th September 2020, covering 32 countries and 28 ISIC industries.[8]

Table 2 presents the detailed description of the variables. Columns (5) – (9) provide summary statistics that reveal important features of our sample. For example, in panel A1 that corresponds to sales outcomes, the first row of column (6) indicates that the average answer of firms to the question *"Is the firm currently open (1), temporarily closed (2) or permanently closed (3)?"* is 2.84, implying that most of the surveyed firms closed during the outbreak. Rows 4 and 5 indicate that on average the closure period is about two months (7.43 weeks) and sales are reduced by a staggering 40%. The first row of panel A2 reveals that most firms reported a fall in total working hours per week. For manufacturing firms, the average monthly output as a share of full-capacity output is 60%, implying a 40% reduction. Panel A3 shows that most firms reduced the total number of temporary workers. About 15% of workers took leave or quit due to illness, childcare, or mobility restrictions, 10% were laid off, and 20% were furloughed during the pandemic.

[7] The survey teams (national private contractors) re-contact all firms sampled in the immediate baseline pre-2020 rounds using stratified random sampling. Survey modes are online interviews with phone-call follow-up. The universe of inference is all registered establishments with five or more employees that are engaged in one of the following activities defined using ISIC 3.1: Manufacturing, construction, services, transport, storage, and communication and information technology.

[8] Note that we do not use panel data in our study. Our choice is justified by two factors. First, since the follow-up interviews are only for firms from the immediately previous rounds and attrition rates for even-earlier rounds are higher, merging data with earlier rounds significantly reduces our sample sizes. Second, by construction, the questions related to outcome variables (i.e., performance during the pandemic) are only available in the 2020 follow-up round. Therefore, information from even-earlier rounds is peripheral to our main research question, viz., how pre-2020 characteristics affect post-2020 firm resilience.

Table 2. Variable Descriptions and Statistics

Var. code	Questionaire (likert values provided in square brackets for categorical question)	Units/Types	Question code	Full sample			Have no website (WEB = 0)		Have website (WEB = 1)		Diff. in mean (9) – (11)
				Obs. (#Firms)	Mean	SD	Obs.	Mean	Obs.	Mean	t-stat (S.E)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Dependent/Outcome variables (2020 round)											
A1. Module: Sales											
SALE1	Is the firm currently open [1], temporarily closed [2] or permanently closed [3]?	Ordered categorical	COVb0	12,990	2.84	0.47	4,790	2.77	8,167	2.88	-0.11*** (0.01)
SALE2	(If is currently open or was temporality closed), did the firm close temporarily due to COVID-19 [1] or not [0]?	Binary	COVb1a	11,415	0.40	0.49	3,971	0.45	7,417	0.38	0.07*** (0.01)
SALE3	(As above), did sales decrease [1], remain the same [2], or increase [3] compared with 2019?	Ordered categorical	COVb2a	12,018	1.38	0.64	4,314	1.31	7,672	1.42	-0.11*** (0.01)
SALE4	(As above), number of weeks of closure due to COVID-19	Continuous, # weeks	COVb1b	5,591	7.43	5.13	2,286	7.93	3,285	7.06	0.87*** (0.14)
SALE5	(As above), percentage of sales increase or decrease compared with 2019	Continuous, %	COVb2b, COVb2c	9,173	-39.34	34.76	3,398	-44.45	5,749	-36.26	-8.19*** (0.75)

Var. code	Questionaire (likert values provided in square brackets for categorical question)	Units/Types	Question code	Full sample			Have no website (WEB = 0)		Have website (WEB = 1)		Diff. in mean (9) – (11)
				Obs. (#Firms)	Mean	SD	Obs.	Mean	Obs.	Mean	t-stat (S.E)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A2. Module: Production											
PROD1	Did total weekly work hours decrease [1], remain the same [2], or increase [3] compared with the same period in 2019?	Ordered categorical	COVc2a	12,058	1.54	0.57	4,325	1.48	7,701	1.57	-0.09*** (0.01)
PROD2	Output produced last month as a share of full capacity (asked manufacturing firms only)	%	COVc1	5,894	63.01	28.56	1,848	57.43	4,034	65.59	-8.16*** (0.80)
A3. Module: Labour											
WORK1	Since the outbreak of COVID-19, did the total number of temporary workers decrease [1], remain the same [2], or increase [3]?	Ordered categorical	COVd3b	11,358	1.79	0.49	4,062	1.75	7,265	1.80	-0.05*** (0.01)
WORK2	Share of workers took leave for more than 5 days or quit due to illness, childcare interruption, or mobility restrictions linked to COVID-19	Continuous, % of Dec-2019 workforce	COVd4	3,720	15.44	29.96	1,487	17.91	2,222	13.72	4.19*** (1.00)
WORK3	Share of workers laid off due to COVID-19	Continuous, % of Dec-2019 workforce	COVd6	3,712	9.62	26.93	1,472	10.96	2,229	8.72	2.24** (0.90)

Var. code (1)	Questionaire (likert values provided in square brackets for categorical question) (2)	Units/Types (3)	Question code (4)	Full sample Obs. (#Firms) (5)	Full sample Mean (6)	Full sample SD (7)	Have no website (WEB = 0) Obs. (8)	Have no website (WEB = 0) Mean (9)	Have website (WEB = 1) Obs. (10)	Have website (WEB = 1) Mean (11)	Diff. in mean (9) – (11) t-stat (S.E) (12)
WORK4	Share of workers furloughed since the outbreak of COVID-19 begins	Continuous, % of Dec-2019 workforce	COVd8	6,741	19.57	34.10	2,317	22.15	4,404	18.14	4.01*** (0.87)
B. Explanatory variable of interest (pre-2020 rounds)											
WEB	Own a website or a social-media page	Binary	c22b	12,957	0.63	0.48	4,790		8,167		
C. Instrumental variable (pre-2020 rounds)											
POWER	In a typical month, how many power outages did this establishment experience?	# outages	c7	4,321	4.78	11.41	4,348	0.20	2,720	4.41	1.01*** (0.36)
D. Mechanism variables (2020 round)											
Module: Production (asked temporarily-closed and/or currently-opened firms only)											
MECH1	Started or increased business activity online [1] or not [0]	Binary	COVc4a	12,099	0.25	0.43	4,348	0.20	7,719	0.28	-0.09*** (0.01)
MECH2	Started or increased delivery or carry-out of goods or services [1] or not [0]	Binary	COVc4b	12,397	0.22	0.42	4,482	0.22	7,883	0.23	-0.01* (0.01)
MECH3	Started or increased remote work arrangement for its workforce [1] or not [0]	Binary	COVc4c	12,398	0.31	0.46	4,484	0.22	7,882	0.37	-0.14*** (0.01)
MECH4	Current share of online sales out of total sales	Continuous, %	COVc5	11,286	8.32	19.30	4,090	6.91	7,164	9.12	-2.21*** (0.38)

Var. code	Questionaire (likert values provided in square brackets for categorical question)	Units/Types	Question code	Full sample			Have no website (WEB = 0)		Have website (WEB = 1)		Diff. in mean (9) – (11)
				Obs. (#Firms)	Mean	SD	Obs.	Mean	Obs.	Mean	t-stat (S.E)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MECH5	Current share of workforce working remotely	Continuous, %	COVc6	12,075	6.86	17.74	4,351	5.09	7,692	7.84	-2.74*** (0.34)
E. Control variables (pre-2020 rounds)											
E1. Firm-level factors											
PCAP	Share of working capital financed from internal funds or retained earnings	Continuous, %	k3a	12,084	74.42	31.25	4,469	76.63	7,598	73.15	3.48*** (0.59)
HCAP	Share of permanent, full-time production workers in unskilled jobs	% of pre-2020 workforce	l4b	5,784	19.40	24.00	1,839	18.45	3,937	19.80	-1.36** (0.68)
GROWTH	Growth rate of annual sales (in local currency units) over the last three years pre-2020	Continuous, %	n3	9,638	9.96	30.33	3,415	7.65	6,204	11.25	-3.60*** (0.64)
SIZE	Firm size: Small [1], medium [2], large [3]	Categorical	a6b	12,990	1.73	0.78	4,790	1.49	8,167	1.87	-0.38*** (0.01)
AGE	Firm age	# years	b6b	12,693	21.18	15.09	4,666	18.33	8,006	22.86	-4.53*** (0.28)
OWN	Firm ownership indicators: Domestic private [1], foreign private [2] and other types (including public-owned firms) [3]	%, converted to categorical	b2a, b2b, b2c, b2d	12,741	1.18	0.50	4,698	1.14	8,017	1.21	-0.07*** (0.01)

Var. code	Questionaire (likert values provided in square brackets for categorical question)	Units/Types	Question code	Full sample			Have no website (WEB = 0)		Have website (WEB = 1)		Diff. in mean (9) – (11)
				Obs. (#Firms)	Mean	SD	Obs.	Mean	Obs.	Mean	t-stat (S.E)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
COMP	Main market for main product: Local [1], national [2], international [3]	Categorical	e1	11,444	1.73	0.69	4,004	1.55	7,420	1.83	-0.28*** (0.01)
E2. Country and industry-level factors											
ESUPP	Daily Economic Support Index	Index, 0 – 100		12,701	52.91	23.24	4,655	52.90	8,013	52.88	0.02 (0.43)
CASES	Daily growth rate of new cases per million pp.	Continuous, %		12,990	36.42	51.53	4,790	31.14	8,167	39.57	-8.42*** (0.94)
S	Sectoral indicators: Services [1], Manufacturing [2]	Categorical	COVa0	12,990	0.50	0.49	4,790	0.44	8,167	0.54	-0.11*** (0.01)

Notes: This table lists, explains and provides summary statistics for all variables used in this study, together with the corresponding questionnaire codes. Note that the sum of columns (8) and (10) does not necessarily equal the value in column (5) due to unanswered questions/missing observations in both the control group (firms without a website) and treatment group (firms with a website). Column (12) presents the t-statistics of the tests for the differences in means between these groups. The corresponding standard errors are in parentheses.

Sources: All data are provided by the World Bank (2020c), except for the daily Economic Support Index, which comes from a research team at the Blavatnik School of Government, University of Oxford (Hale et al., 2020) and daily new COVID-19 cases per million, which comes from a research team at John Hopkins University (Dong et al., 2020).

Table 3. Country-Specific Firm Performance During COVID-19

	Survey module			Sales					Production		Labour			
Country	GDP p.c ($)	Obs.	% service firms	SALE1	SALE2	SALE3	SALE4	SALE5	PROD1	PROD2	WORK1	WORK2	WORK3	WORK4
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1. Italy	42,492	453	38.9	19.0	42.4	68.0	3.5	38.6	60.5	26.9	11.0	0.0	0.0	0.0
2. Czech	40,862	405	37.8	1.7	22.2	52.6	2.0	8.9	32.3	4.2	16.3	6.2	2.7	2.7
3. Cyprus	39,545	171	62.0	5.8	45.6	73.1	2.3	32.7	35.7	14.6	7.6	3.5	0.0	42.7
4. Slovenia	39,088	249	62.7	0.8	34.9	56.6	2.8	10.8	47.0	6.4	28.5	6.8	4.0	20.9
5. Lithuania	37,231	214	63.1	0.5	43.0	45.8	4.7	8.9	19.2	4.2	9.3	8.9	2.8	38.3
6. Estonia	36,927	272	63.2	0.7	16.9	41.5	1.8	6.2	25.7	4.8	8.1	4.8	2.9	11.0
7. Poland	33,221	1,005	26.6	9.3	12.9	52.1	3.3	8.8	33.3	9.7	17.6	6.1	3.8	10.6
8. Hungary	32,945	630	40.0	2.2	11.1	49.5	2.5	8.9	34.6	7.8	3.3	4.0	4.0	8.9
9. Latvia	30,898	244	66.0	6.6	4.5	27.0	1.2	5.7	25.4	24.2	34.8	9.4	1.6	4.1
10. Romania	29,941	532	38.5	3.6	23.1	57.3	3.0	15.0	27.6	12.4	2.1	3.8	2.8	35.3
11. Greece	29,799	532	47.9	4.1	29.1	68.8	3.0	31.4	41.4	15.8	12.4	2.6	0.8	48.9
12. Croatia	28,602	351	62.1	3.1	26.5	55.8	2.3	14.8	21.4	7.7	9.4	0.6	0.6	2.6
13. Russia	27,044	1,191	31.6	8.0	57.4	67.4	2.2	14.1	52.6	11.0	35.1	0.0	0.0	0.0
14. Bulgaria	23,174	559	41.7	8.6	22.7	64.2	3.6	21.8	39.9	13.6	3.0	5.2	7.2	25.0
15. Belarus	19,150	551	43.0	4.5	8.0	49.4	1.6	14.3	22.9	11.3	3.8	2.0	1.6	6.9
16. Georgia	14,992	514	64.8	24.1	37.7	70.6	13.6	44.7	62.6	17.7	23.9	0.0	0.0	0.0
17. Lebanon	14,552	316	43.0	12.7	54.7	0.0	13.3	0.0	0.0	40.8	0.0	0.0	0.0	0.0
18. Albania	13,965	347	62.0	13.5	51.3	82.4	14.1	52.4	48.4	8.6	51.6	11.5	6.1	8.6
19. Moldova	13,050	286	61.5	14.3	38.5	88.1	0.3	56.6	76.2	23.4	2.1	0.0	0.0	0.0
20. Mongolia	12,317	314	65.9	18.2	32.5	72.6	21.0	30.3	51.6	3.8	29.9	8.6	9.6	16.6

Table 3. Country-Specific Firm Performance During COVID-19 (cont')

	Survey module			Sales					Production		Labour			
Country	GDP p.c ($)	Obs.	% service firms	SALE1	SALE2	SALE3	SALE4	SALE5	PROD1	PROD2	WORK1	WORK2	WORK3	WORK4
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
21. Jordan	10,071	564	52.0	16.5	79.8	76.8	29.3	55.1	47.0	24.1	14.7	15.2	2.5	0.0
22. El Salvador	8,776	405	44.2	26.4	42.5	82.7	26.2	61.7	82.2	37.3	31.1	5.9	2.5	25.2
23. Guatemala	8,637	203	60.6	18.2	53.2	84.2	17.7	48.3	82.3	21.7	48.8	7.9	8.9	33.0
24. Morocco	7,515	873	59.1	18.1	55.6	75.7	29.2	50.3	39.4	18.6	29.0	11.9	4.0	30.5
25. Honduras	5,728	169	65.7	33.1	52.7	84.6	35.5	60.9	84.6	22.5	39.6	7.1	14.2	32.0
26. Nicaragua	5,407	190	61.6	8.4	23.2	78.4	5.3	45.3	65.8	21.6	32.1	5.8	11.1	13.7
27. Zambia	3,470	563	71.9	21.5	14.2	81.3	8.2	46.2	56.7	15.1	39.3	7.6	18.8	0.0
28. Zimbabwe	2,836	549	51.2	12.8	68.1	89.1	8.4	54.8	86.7	32.6	47.9	16.4	9.3	0.0
29. Guinea	2,562	104	83.7	28.8	17.3	95.2	17.3	67.3	87.5	14.4	66.3	10.6	7.7	36.5
30. Togo	1,597	56	73.2	26.8	8.9	78.6	1.8	57.1	76.8	23.2	57.1	16.1	3.6	14.3
31. Chad	1,580	107	48.6	83.2	1.9	82.2	9.3	40.2	58.9	17.8	47.7	20.6	15.9	39.3
32. Niger	1,225	71	71.8	18.3	16.9	90.1	9.9	53.5	84.5	7.0	25.4	8.5	2.8	31.0
Mean	19,350	406	55.2	14.8	32.8	66.9	9.4	33.3	50.3	16.4	24.7	6.8	4.7	16.8
S.D	13,778	260	13.4	15.2	19.4	20.1	9.6	20.6	23.3	9.4	18.2	5.2	4.8	15.4

Notes: This table presents measures of country-specific firm performance during the COVID-19 pandemic in our sample along three dimensions as captured by the three survey modules described in Table 2. The countries are ordered by their 2019 GDP per capita [column (2)]. *Sale outcomes*: Columns (5) – (9) document the shares of firms that, in this order, reported temporary or permanent closures, indicated a closure due to COVID-19, experienced sales decrease, were out of business for more than half the time since 2020 begins, and experienced at least 50% sale reduction. *Production outcomes*: Columns (10) – (11) document the shares of firms that experienced decreasing weekly work hours and had production capacity fall below 50%. *Labour outcomes*: Columns (12) – (15) document the shares of firms that experienced a reduction in the number of temporary workers, and as a result of the pandemic, had at least 25% of their workforce either (i) quit/leave (ii) laid-off or (iii) furloughed.

We are interested in examining whether firms' website ownership, which is a proxy for their capability to shift their businesses online, is a driver of economic resilience during and post-COVID-19. Intuitively, this is why we examine the statistical association between website ownership and firm performance. As a first pass, we look at simple t-statistics for the tests of differences in means of outcomes between firms with and without a website or a social media page. Column (12) of Table 2 shows that website owners significantly outperform non-owners in all outcome dimensions. For instance, the probability of temporary closure is 7% higher and the reduction in sales is 8.2 percentage points greater for firms with no website. Interestingly, the differences in both mechanism variables (panel D) and pre-COVID firm characteristics (panel E) are statistically significant except for government's economic support. This implies that using website ownership as an independent variable could result in self-selection biases in our estimates since the choice of owning a website is not random and reflects factors that are strongly linked to determinants of economic resilience. These include both observables such as the endowment of physical or human capital and unobservables. Therefore, using the number of monthly power outages as an instrumental variable (panel C) is justified.

To conclude this section, we briefly discuss Table 3 which lists all countries surveyed as well as the summary statistics of firm performance measures. The measures are constructed based on the outcome variables described in Table 2. To facilitate comparison, all are defined as country-level shares of the total number of firms. The second-to-last row of Table 2 shows that, on a cross-country average basis, about 15% of the surveyed firms experienced temporary or permanent closure, 33% reported temporary closures due to the pandemic, and 67% and 50% had their sales and work hours reduced, respectively. In addition, there are firms that had more than a quarter of their workforce quit or take leave (7%), laid off (5%), or furloughed (17%). However, these averages mask the heterogeneity of country-specific performance.

5. RESULTS AND DISCUSSION

5.1. Impact of Website Ownership on Firms' Resilience during COVID-19

Table 4 summaries our main empirical results. Specifically, we report the marginal effects of website ownerships on several firm performance outcomes using the baseline model in column (4) and IV models in column (5).[9] The estimates from the baseline models are not qualitatively different from those of the IV models, implying that biases,

[9] To conserve space, estimates of control variables' coefficients are not shown in Table 4, but are available upon request.

if they exist, are small.

Table 4. Effects of Website Ownership, Online Business and Remote Workforce on Firm Performance During COVID-19

Dependent variable				**Model**	**Marginal effect**			
					Website ownership		Online business	Remote working
	Question (1)		ID (2)	(3)	Non-IV (4)	IV (5)	IV (6)	IV (7)
Probability of	Permanent closure		SALE1	Ordered probit	-2.70***	-2.88***		
					(0.48)	(0.65)		
	Temporary closure				-3.50***	-3.69***		
					(0.59)	(0.79)		
	Remaining open				6.20***	6.57***		
					(1.03)	(1.40)		
If currently opened or temporarily closed	Probability of temporary closure		SALE2	Probit	-8.02***	-7.08***	-21.31***	
					(1.80)	(2.20)	(2.28)	
	Probability that sales …	Decreased	SALE3	Ordered probit	-4.68***	-3.11	-10.36***	
					(1.59)	(1.97)	(2.02)	
		Unchanged			2.59***	1.70	5.84***	
					(0.90)	(1.09)	(1.21)	
		Increased			2.10***	1.42	4.53***	
					(0.69)	(0.89)	(0.84)	
	Number of weeks of temporary closure		SALE4	Linear	-0.53*	-0.92***	-1.14***	
					(0.28)	(0.34)	(0.33)	
	% change in sales		SALE5		7.28***	7.70***	-0.39	
					(1.32)	(1.70)	(1.69)	

Table 4. Effects of Website Ownership, Online Business and Remote Workforce on Firm Performance During COVID-19 (cont')

Dependent variable			**Model**	**Marginal effect**			
				Website ownership		Online business	Remote working
Question (1)		ID (2)	(3)	Non-IV (4)	IV (5)	IV (6)	IV (7)
Probability of number of weekly work hours …	Decreased	PROD1	Ordered probit	-6.65***	-6.10***		
				(1.70)	(2.07)		
	Unchanged			5.19***	4.76***		
				(1.36)	(1.64)		
	Increased			1.46***	1.34***		
				(0.36)	(0.44)		
% of full capacity		PROD2	Linear	0.08***	2.45*		
				(0.02)	(1.27)		
Probability of number of temporary workers ...	Decreased	WORK1	Ordered probit	-5.10***	-4.88***		-0.52
				(1.45)	(1.67)		(1.51)
	Unchanged			3.99***	3.81***		0.40
				(1.17)	(1.34)		(1.15)
	Increased			1.11***	1.06***		0.12
				(0.30)	(0.34)		(0.36)
Due to COVID-19, the share of workers that …	Leave/quit	WORK2	Linear	-1.51	1.12		-0.30
				(2.07)	(3.50)		(3.73)
	Are laid-off	WORK3		-2.63**	-2.06		-1.34
				(1.11)	(1.44)		(1.44)
	Are furloughed	WORK4		-0.46	-3.18*		-3.44*
				(1.42)	(1.83)		(1.83)

Notes: 1. The results for probit and ordered probit models are average marginal effects and are multiplied by 100. These are the changes in the probability of a firm exhibiting a particular outcome [see column (1)] when it decides to either (i) own a website [columns (4) – (5)], adopt an online business model [column (6)] or allowing for a remote workforce [column (7)], holding other factors constant. The results for linear models are second–stage results of two-stage least square estimations. See Table 2 for variable definitions and Section 3 for detailed discussion of the models.

2. Robust standard errors are in parentheses. Statistical significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

3. For presentation purpose, estimated coefficients of control variables are omitted but available upon request.

Column (5) of this table shows that website ownership significantly mitigates the adverse impact of the crisis on almost all firm performance measures. For example, compared with firms that do not own a website or social media page, those that do are 2.88% and 3.69% less likely to suffer permanent and temporary closures while 6.57% more likely to remain open. Among those that are currently open or have temporarily closed, the probability of COVID-19-induced closure is 7.08% lower for website owners. Interestingly, the effect of website ownership on the probability that sales decreased, remained the same, or increased are not statistically significant for IV estimates, although they are significant for baseline estimates.

In addition, website owners experienced 0.92 weeks less temporary closure and boosted their sales by 7.7 percentage points compared to non-owners. Website owners are 6.1% less likely to have their weekly work hours reduced, and 4.76% and 1.34% more likely to have them unchanged and increased, respectively. As a result, their production capacity utilization is 2.45 percentage points higher. Finally, the share of workers that are furloughed is 3.18 percentage points lower in firms with a website. The effects on workers quitting jobs and being laid off due to the pandemic are not significant.

5.2. The Role of E-Commerce and a Remote Workforce

Having established a link between website ownership and online business development and remote work arrangement, we directly examine the impact of the latter on firm performance. Columns (6) and (7) of Table 4 present the results. Adopting an online business model significantly reduces the probability of temporary closure by 21.31% and the probability of reduced sales by 10.36%. The probabilities of unchanged or increased sales are 5.84% and 4.53% higher. Remote work arrangement, on the other hand, does not significantly affect the number of temporary workers or the shares of workers who left or quit or were laid off. However, working remotely reduced the share of furloughed workers by a significant 3.44 percentage points.

5.3. Country- and Industry-Effects of Website Ownership

To conclude this section, we propose an approach that directly quantifies the impact of website ownership in different countries and industries in our sample. For this purpose, we replace the list of control variables contained in the vector X_i (described in Section 3) with a set of country-dummy variables C_i, each of which takes the value 1 if firm i is located in a particular country c $(c = 1, \dots, 32)$ and zero otherwise. The corresponding set of industry-dummy variables, denoted as S_i, consists of components equal 1 if firm i operates in a particular ISIC sector s $(s = 1, \dots, 28)$. Then, we interact these dummies with website ownership, resulting in the following models:

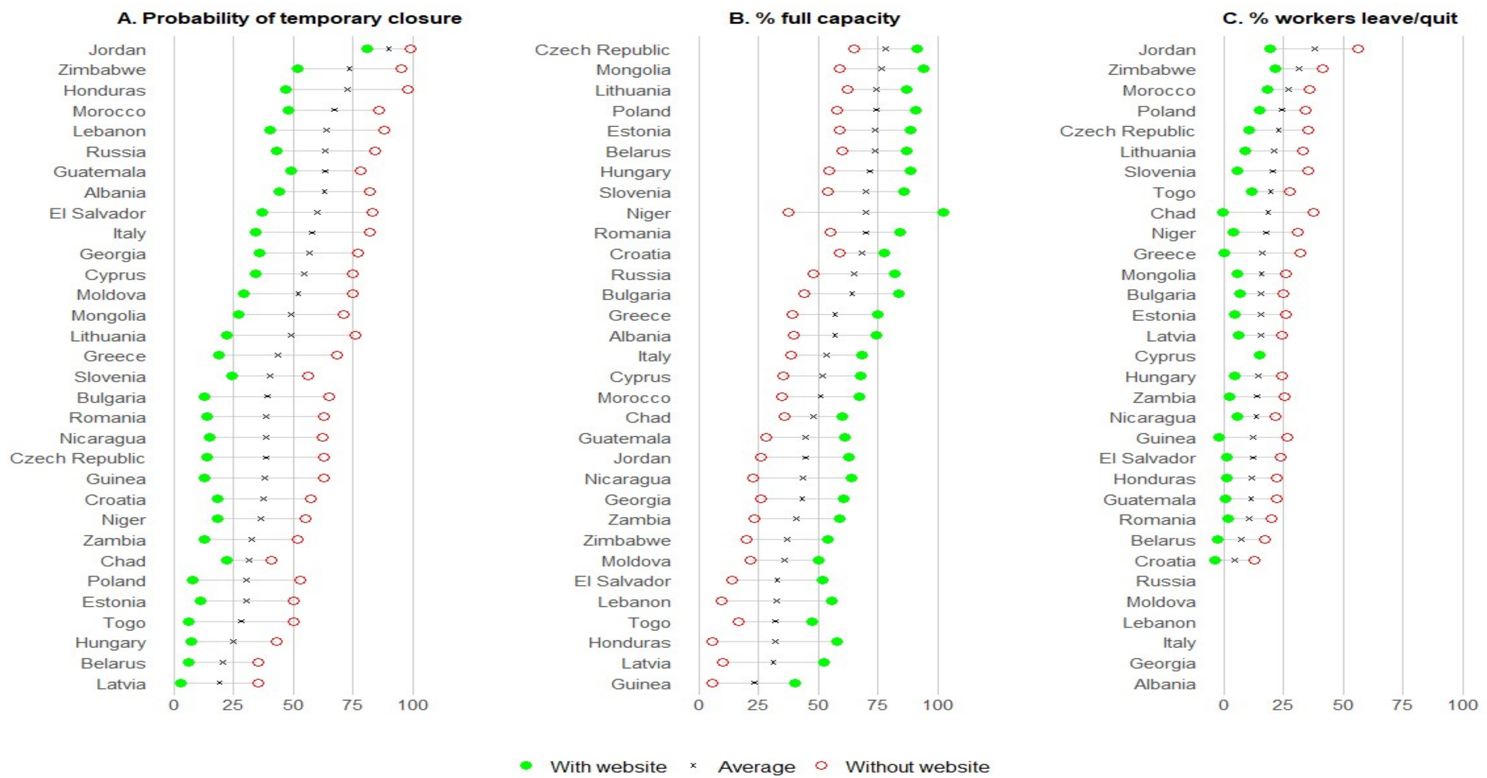
$$y_i = a y_{2i} + C_i' b + (y_{2i} \times C_i') c + \varepsilon_i,$$

$$y_i = a y_{2i} + S_i' d + (y_{2i} \times S_i') e + \varepsilon_i, \tag{9}$$

where y_i is either an observed dependent variable (linear model) or an unobserved one (probit models). We are interested in the coefficients $\boldsymbol{c}$ and $\boldsymbol{e}$. To directly quantify the digital divide effect, in each country c and industry s, based on the IV estimates of (9) we compute the predicted values of representative outcomes. These include (i) the probability of temporary closure (SALE2); (ii) the share of full capacity utilization (PROD2) and (iii) the share of workers who leave or quit (WORK2) in the website firms and non-website firms.

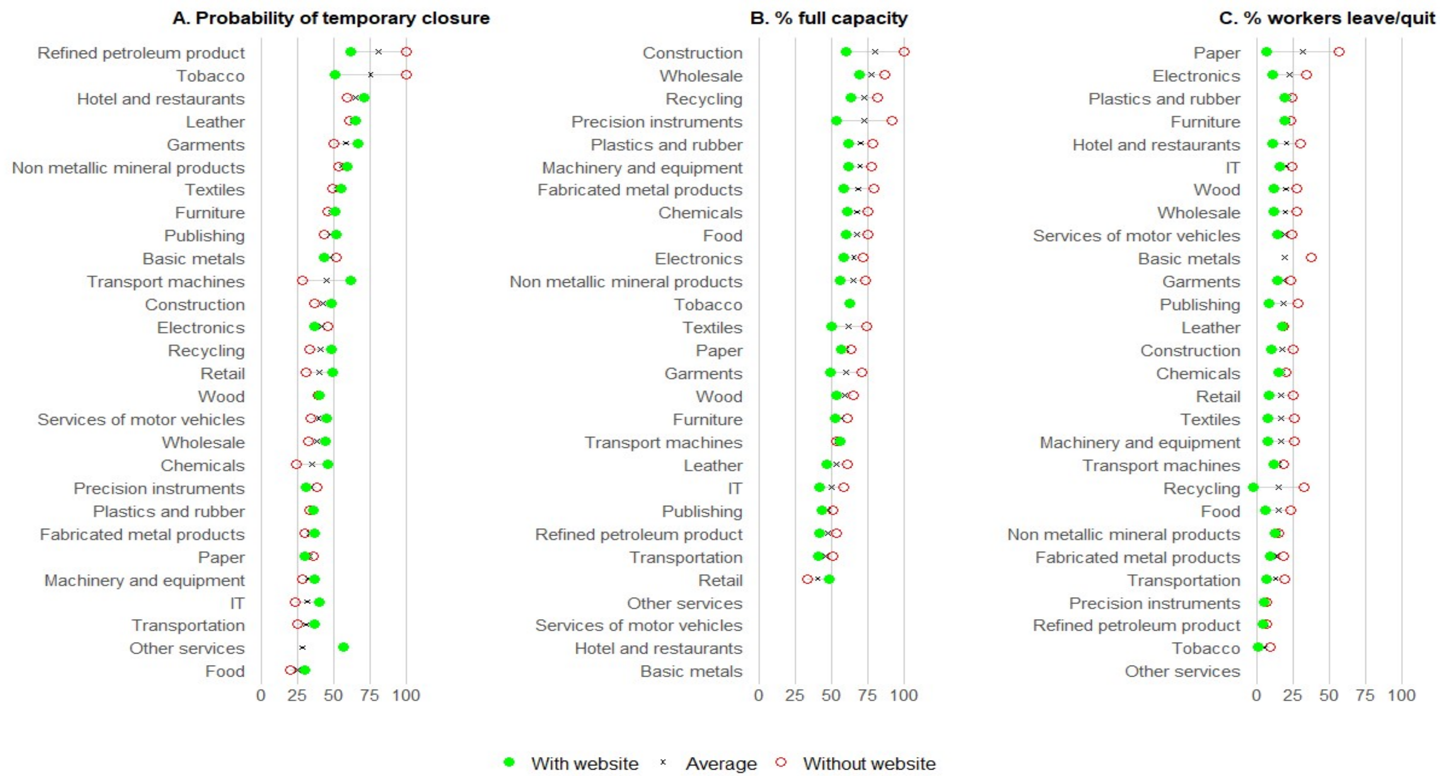
The predicted values for both groups are visualized in Figures 1 and 2. The countries are ordered by the averages of website owners and non-owners. These figures clearly highlight the differences between the two types of firms and provide a simple but revealing gauge of the width of the digital divide in the COVID-19 era. The most salient observation is the fact that website owners perform better than non-owners in all three dimensions: They are less likely to experience temporary closure, more able to keep up production, and suffered a smaller reduction in workforce. Second, somewhat surprisingly, while the digital divide effect is substantial and heterogeneous across countries, income level is not a strong predictor of the divide. That is, both poor and rich countries can have either small digital divides (e.g., Chad and Jordan) or large digital divides (e.g., Italy, Czech Republic, Nicaragua, and Guinea). Additionally, the ranking of countries varies with the performance measure. For example, the gap in the probability of temporary closure is largest for Lithuania (54%), while the gap in capacity utilization and share of workers who leave or quit are largest for Niger (65%) and Chad (37%), respectively. Countries with the smallest firm-level gap between website firms and non-website firms include Jordan (18% gap in the probability of temporary closure), Croatia (19% gap in capacity utilization) and Cyprus (0.21% gap in workers leaving or quitting). Interestingly, Figure 2 suggests that the corresponding gaps in industries are much smaller, though not less dispersed, than the gaps in countries. The cross-industry mean and standard deviation of the closure probability gaps are 14.8% and 13.6%, compared with cross-country mean and standard deviation of 41% and 8.8%. For capacity utilization, the mean and standard deviation are 15.8% and 9.3% across industries and 34.5% and 8.5% across countries. Finally, the corresponding figures for the number of workers who leave or quit are 14.5% and 11.6% for industries and 21.9% and 7.4% for countries. To sum up, once an industry is severely affected by the COVID-19 pandemic, website ownership does not significantly mitigate the adverse impact of COVID-19 once an industry is hit hard by the pandemic.[10]

[10] For robustness, we also compute the corresponding *marginal effects* of going from not owning a website to owning one and the results are available upon request. In general, the magnitude of these effects also points to a digital divide, and their statistical significance is consistent with the implications of differences in predicted outcomes: The marginal effects are significant for most countries, but not significant for most industries.



Notes: For each country, this figure presents predicted values of three selected COVID-19-related enterprise outcomes: The probabilities of temporary closure (SALE2), firm production as a share of full capacity (PROD2) and the share of firm's workforce leave or quit (WORK2). Each outcome is predicted for two subsamples of firms that own and do not own a website. These values are estimated coefficients of relevant interaction terms as featured in Equation (9).

Figure 1. Quantifying the Digital Divide in the COVID-19 Era: Predicted Country Outcomes Conditioned on Website Ownership



Notes: For each industry, this figure presents predicted values of three selected COVID-19-related enterprise outcomes: The probabilities of temporary closure (SALE2), firm production as a share of full capacity (PROD2) and the share of firm's workforce leave or quit (WORK2). Each outcome is predicted for two subsamples of firms that own and do not own a website. These values are estimated coefficients of relevant interaction terms as featured in Equation (9).

Figure 2. Quantifying Digital Divide in the COVID-19 Era: Predicted Industry Outcomes Conditioned on Website Ownership

6. CONCLUSIONS

The development of the digital economy will bring many opportunities for developing countries. The impact of the digital transformation depends on the development and readiness of technology, along with policy design and implementation. However, developing countries are also facing many challenges, including the lack of resources to develop information technology infrastructure and a digital ecosystem. The digital transformation also raises the possibility of a productivity paradox. Productivity effects would not be generated if digital technology is still in the installation phase during which new technologies are driven by the creation of new infrastructure and superior ways of doing things. Growth occurs only during the deployment phase when a new paradigm is widely diffused and becomes common practice across organizations, enabling its full potential in terms of economic and business growth, productivity, and profitability (Van Ark, 2016). As such, developing countries need to make efforts to overcome existing capacity limitations and promote the development of the digital economy.

In the ongoing global pandemic, digital technologies have become a critical enabler of connectivity, thereby facilitating the continuity of our regular lives. When countries imposed lockdowns and stay-at-home orders, entire populations turned to their digital devices as a lifeline. Digital technology enabled a wide range of in-person activities, including telework, telemedicine, food delivery and logistics, contactless payments, online meetings, and remote learning and entertainment. Until global herd immunity is achieved through sufficient progress on vaccination, online arrangements will continue to be the new normal. Although the extent of online arrangements is expected to diminish once the pandemic is contained (Barrero et al. 2021), the large-scale natural experiment of digitalization during COVD-19 will no doubt fundamentally change our living and working habits for a long time to come. Hence, the need for a reliable and sustainable digital infrastructure is greater than ever as the world gradually recovers from the unprecedented pandemic.

If the financial constraints faced by some market players hamper much-needed investment in digital infrastructure, the societal and economic consequences could be large and persistent (Katz, 2020). Solid research evidence on the benefits of digital infrastructure investment can provide guidance for governments to consider such investment. In this paper, to generate such evidence, we examine the impact of the COVID-19 pandemic on the economic resilience of firms operating in developed and developing countries.

Our research fills in a major gap in the literature about Information Technology (IT) for development, namely the quantification of the impact of the Digital Divide across a large number of firms, industries and countries during a crisis. This topic was not studied extensively before, due to the lack of available data and more importantly, the lack of a dramatic event that can reveal the true effect of the Digital Divide. The novel and comprehensive data collated by the World Bank's Enterprise Surveys Unit allow us to not only understand the effects of the pandemic on several performance dimensions, including revenue, production, and labor outcomes, but also identify key firm-level determinants of such performance. Furthermore, given the peculiar, and arguably unique, nature of the current crisis that upended conventional business models based on social interaction, we focus on examining one important factor that contributes to firm resilience, i.e., access to online business infrastructure.

Our paper also advances the IT for development literature with regards to the methodological aspect. In this paper, we employed econometric models that use access to a stable power supply as an instrument for website/social media ownership. Firms which have more stable power supply can support better digital infrastructure and subsequently are more successful commercially. Without this instrument, we could not reliably identify the causal effect of digital infrastructure due to model endogeneity concern. This feature of our models represents a significant contribution to both academia and practitioners who seek to understand the broader impact of IT on modern economic development.

In accordance with previous research, we document substantially heterogeneous effects of the pandemic on economic performance across countries and industries. On average, firms in poorer countries and service-intensive industries were more likely to be affected by the social distancing restrictions. In particular, they are significantly more likely to experience permanent or temporary closures, reduced sales and production capacity, and a reduced workforce. After controlling for the local prevalence of the disease and several firm-level characteristics, and using robust identification strategies, we consistently found that firms with access to digital infrastructure are better prepared for a switch to online business models and a remote workforce than firms without such access. This preparedness eventually translates into mitigation of the pandemic's adverse effects on business and better firm performance.

The findings of our paper regarding the impact of digital technology on business resilience during COVID-19 entail important policy implications. First, since we find the effect of online commerce and remote workforce on resilience to be the highest for middle-income countries, the returns to modernizing the digital infrastructure may be highest in those countries. Secondly, it has been documented that small-and-medium enterprises (SME) often lack the funds to continually enhance their technologies (Strack et al. 2020). Given our finding that the performance of SMEs improved when they have access to website ownerships, governments may consider supporting them with subsidized loans or investment tax breaks to digitally enable their workforce. Finally, we found that while access to online platform infrastructure enhances the potential for e-commerce and remote working, it does not improve online delivery activities significantly. This result reflects the substantial effect of stay-at-home restrictions which suppressed even minimal physical contact, and implies that certain industries that rely on at least some physical contact, such as food delivery, will suffer strong adverse effects, regardless of the degree of digitalization. Since many of these industries are important for the supply chain, they may need support policies tailored to their specific operating model.

We conclude our paper with discussions of caveats and future research possibilities. Despite the fact that our data cover a wide range of economies and industries that were affected by the pandemic, the lack of time-varying data may limit our understanding of the evolving impact of the pandemic on firm resilience. In the future, once results from additional surveys become available, analysis of the performance of firms over time would be an interesting topic for research. Another future research direction would be to assess the impact of government policies that supported the effort of firms to shift their activities online.

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