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ABSTRACT

We examine the adverse impact of coronavirus disease (COVID-19) on the performance of more than 12,000 firms in 32 countries along several dimensions; namely, revenue, production, and labor outcomes. We 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. To explain the diverse firm performance, we identify key factors that significantly contribute to firm resilience during the COVID-19 pandemic, especially access to digital infrastructure. After controlling for firm characteristics, macroeconomic conditions, and pandemic prevalence, we found that firms that have access to digital infrastructure performed better than those that do not. The key channel is an enhanced capacity to adopt electronic commerce business models and employ a larger share of the remote workforce, which boosts resilience during the pandemic when social distancing measures are mandated.

Keywords: organizational reform, digital infrastructure, technology transformation, working from home, labor productivity

JEL codes: M11, L25, H12

I. INTRODUCTION

The coronavirus disease (COVID-19) pandemic has upended lives and economies worldwide. 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 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 COVID-19 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 communications technology (ICT) or digital technology, it is not simple to clearly define the concept of the digital economy. For instance, according to the Organisation for Economic Co-operation and Development (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.” Bukht 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 gross domestic product in this decade (Knickrehm et al. 2016).

The vibrant 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, which enables 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 the existing capacity limitations and promote the development of the digital economy. A key precondition for developing the digital economy is investment in digital infrastructure, which includes investment in ICT infrastructure, energy infrastructure, technology transfer, and human capital (Saka et al. 2021).

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 a 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 10 developed countries during the period 2000–2001 by performing principal components analysis on six factors of digitalization but could not explain the cross-country differences. Meanwhile, Rückert et al. (2020) confirm a growing digital divide across firms in the European Union and the United States. While firms that are digitally inactive are falling behind, digitally active firms are forging ahead. Market concentration is growing, with higher firm markups evident in sectors where digital technology is widely diffused (Calligaris et al. 2018).

COVID-19 creates a unique natural experiment about the effect of the digital divide. The pandemic allows us to observe significant differences in economic performance between digital versus non-digital firms. 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, our results indicate that firms that have access to digital infrastructure performed significantly better than those that do not. Further, we examine the possible channels via which digital access boost resilience, such as e-commerce and remote work.

The contribution of our study to the existing literature is threefold. 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

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

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 management.

The remainder of this study is organized as follows. Section II reviews the three strands of interrelated literature on the role of the pandemic in accelerating digital transformation. Section III discusses the various models that are used in our empirical analysis. Section IV describes the data and then reports some preliminary analyses. Section V reports and discusses the main empirical results about the impact of access to digital infrastructure on firms' resilience during the COVID-19 pandemic. Finally, Section VI concludes the paper.

II. RELATED LITERATURE

A. 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 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 true especially for industries that involve social contacts such as aviation, tourism, and hospitality. Many businesses, which suffered business income losses and even insolvency, have laid off workers. Further, the effects of the COVID-19 outbreak vary across firms (Apedo-Amah et al. 2020). Staying in business is difficult, especially for small and medium-sized enterprises (SMEs). Because of social distancing restrictions, many workers are unable to perform their jobs. This has resulted in 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 report of the United Nations Conference on Trade and Development (UNCTAD), 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

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

Amazon, Alibaba, Shopify, and Etsy have grown rapidly during COVID-19, COVID-19 being a major catalyst that amplified the role of e-commerce in the retail sector.

The spread of COVID-19 pandemic and the related containment measures adversely affect productivity (Bartik et al. 2020, di Mauro and Syverson 2020) because of increases in intermediate costs (Bloom et al. 2020). The allocation of resources within countries as well as across sectors and firms is limited because of mobility restrictions and higher transaction costs (Apedo-Amah et al. 2020). Consequently, allocative efficiency and aggregate productivity growth declined. Bloom et al. (2020) estimated that total factor productivity in the United Kingdom's 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.

B. Working from Home and Productivity

Given the high transmission risk of COVID-19, instead of directly operating in offices, many businesses switched to working remotely or work from home (WFH). Interestingly, COVID-19 redirected technical transformation in ways that enhanced remote interactivity (Bloom et al. 2021). For instance, the number of new United States 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 labor productivity of 5% relative to the pre–COVID-19 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 centers of a Fortune 500 online retailer during 2018–2020 (Emanuel and Harrington 2020). Similarly, randomized control trials show that WFH improves the total factor productivity of Ctrip, the People's Republic of China's largest travel agency, by between 20% and 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 2020).

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-19 analysis reveals that productivity declines by 12% for workers who selected WFH (Emanuel and Harrington 2020). 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.

C. 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 enhances their presence in the market by providing a less costly and more efficient supply chain. As a result, the adoption of e-commerce 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 2019–2021, 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 that were 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).

III. METHODOLOGY

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.

A. 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 because of COVID-19 or the share of workers laid off. The model has the form

(1) $$y_{1i} = a y_{2i} + \boldsymbol{X_i'} \boldsymbol{b} + \varepsilon_i,$$

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. $\boldsymbol{X_i} = \{x_{ki}\}(k = 1, \ldots, K)$ 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 Section IV.[4] ε_i denotes an error term with a standard normal distribution. The estimated coefficients of the parameters ω and $\boldsymbol{\beta} = \{\beta_k\}$, respectively, capture the effects of our variable of interest, website ownership, and of the control variables, on firm outcome y_{1i}.

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3 Subsequently, we report in Section V 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).

B. 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

$$(2) \qquad y_{1i}^{*} = ay_{2i} + \boldsymbol{X}_i'\boldsymbol{b} + \varepsilon_i,$$

in which y_{1i}^{*} denotes a continuous latent variable capturing the propensity of firm i exhibiting a particular outcome. $\boldsymbol{X}_i$ 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 $g(y_{1i}^{*})$:

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

For estimation, (3) can be rewritten as

$$(4) \qquad Pr(y_{1i} = 1) = 1 - \Phi(-\omega y_{2i} - \boldsymbol{X}_i'\boldsymbol{\beta}),$$

where Φ denotes the standard cumulative normal distribution function. The parameters ω and $\boldsymbol{\beta}$ 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

$$(5) \qquad \begin{aligned} \frac{\delta Pr(y_{1i}=1)}{\delta y_{2i}} &= Pr(y_{1i} = 1 | y_{2i} = 1) - Pr(y_{1i} = 1 | y_{2i} = 0); \\ \frac{\delta Pr(y_{1i}=1)}{\delta \boldsymbol{X}} &= [\Phi(-\omega y_{2i} - \boldsymbol{X}_i'\boldsymbol{\beta})]\boldsymbol{\beta}. \end{aligned}$$

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 $\boldsymbol{X}_i'$ and in y_{2i} , i.e., going from “no website” to “have website”.

C. 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 Section IV, 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

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

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

$$\text{(7)} \qquad Pr\big(y_{1i} = O_j\big) = \Phi\big(\mathrm{c_j} - \omega y_{2i} - \boldsymbol{X}_i'\boldsymbol{\beta}\big) - \Phi\big(\mathrm{c_{j-1}} - \omega y_{2i} - \boldsymbol{X}_i'\boldsymbol{\beta}\big),$$

where O_j denotes the j-th outcome ($j = 1,2,3$). The coefficients ω and $\boldsymbol{\beta}$ 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

$$\text{(8)} \qquad \begin{aligned} \frac{\delta Pr(y_{1i} = j)}{\delta y_{2i}} &= Pr(y_{1i} = j | y_{2i} = 1) - Pr(y_{1i} = j | y_{2i} = 0); \\ \frac{\delta Pr(y_{1i} = j)}{\delta \boldsymbol{X}} &= \big[\Phi\big(\mathrm{c_j} - \omega y_{2i} - \boldsymbol{X}_i'\boldsymbol{\beta}\big) - \Phi\big(\mathrm{c_{j-1}} - \omega y_{2i} - \boldsymbol{X}_i'\boldsymbol{\beta}\big)\big]\boldsymbol{\beta}. \end{aligned}$$

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 $\boldsymbol{X}_i$ and website ownership, averaged across all firms.

D. 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).

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.

[Insert Table 1 here]

E. Mechanisms of Website Ownership Effect

As discussed in Section I, 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

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

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.

IV. 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.[7] 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 firm-performance measures (World Bank 2020b). 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 2020c).[8] 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 stage.

Importantly, the 2020 follow-up data can be merged with the baseline pre–2020 data with a unique firm identifier. Further, 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

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6 https://microdata.worldbank.org/.
7 For discussions of other advantages, refer to Rodriguez-Meza (2020).
8 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 International Standard Industrial Classification (ISIC) 3.1: manufacturing, construction, services, transport, storage, and ICT.

interviewed between 5 May and 30 September 2020, covering 32 countries and 28 International Standard Industrial Classification (ISIC) industries.[9]

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 2 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 because of illness, childcare, or mobility restrictions, 10% were laid off, and 20% were furloughed during the pandemic.

[Insert Table 2 here]

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-19 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

[9] 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.

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 because of 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. For instance, we see that firms from richer economies tend to be much more resilient than their counterparts from poorer economies (refer also to Figure A1 in the Appendix[10]).

Table A1 of the Appendix presents similar statistics to those of Table 2 for each industry and reveals that firms in industries such as (1) hotels and restaurants; (2) transport machines (3) transport, storage, and communication; and (4) services of motor vehicles suffered more than 45% sales reduction on average. These services are heavily dependent on mobility, which were severely curtained by containment restrictions.[11] In addition, manufacturing sectors that provide inputs for fashion industry, such as leather and textiles, and other labor-intensive sectors, such as construction and furniture, were also among the top 10 most-affected industries.

[Insert Table 3 here]

V. RESULTS AND DISCUSSIONS

A. 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

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[10] The Appendix can be accessed here: http://dx.doi.org/10.22617/WPS220332-2.

[11] Interestingly, as seen in column (4) of Table 1, the share of surveyed firms that operate in the services sectors relative to the manufacturing sector falls as income falls. This is consistent with the dominance of services in the consumption baskets of richer countries (Podkaminer 2011, Vo 2021). In any case, the sampling procedure implemented by the Enterprise Survey Unit was carefully designed to ensure national representativeness (World Bank 2020b).

(4) and IV models in column (5). For presentation purposes, estimates of control variables' coefficients are not shown in Table 4, but are presented in Appendix A2. The estimates from the baseline models are not qualitatively different from those of the IV models, implying that biases, if they exist, are small.

Column (5) of Table 4 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 because of the pandemic are not significant.

[Insert Table 4 here]

B. The Role of E-commerce and a Remote Workforce

In Table A6 of Appendix A2, we report IV estimates that capture the effect of website ownership on several mechanism variables. We find that, compared with non-owners, website owners are 5.33% more likely to start or increase their online business activities and 8.76% more likely to facilitate remote work arrangements for their workers. The shares of online sales and the share of remote workers are 1.57 and 1.3 percentage points higher for website owners. Interestingly, the effect on delivery or carry-out of goods and services is not significant.

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.

C. 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 $\boldsymbol{X}_i$ (described in section III) with a set of country-dummy variables $\boldsymbol{C_i}$, 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 $\boldsymbol{S_i}$, 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:

$$
\begin{aligned}
y_i &= a y_{2i} + \boldsymbol{C}_i' \boldsymbol{b} + (y_{2i} \times \boldsymbol{C}_i')\boldsymbol{c} + \varepsilon_i; \\
y_i &= a y_{2i} + \boldsymbol{S}_i' \boldsymbol{d} + (y_{2i} \times \boldsymbol{S}_i')\boldsymbol{e} + \varepsilon_i,
\end{aligned}
\tag{9}
$$

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 Figure 1 and Figure 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).

[Insert Figure 1 here]

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.[12]

[Insert Figure 2 here]

VI. CONCLUDING REMARKS

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

[12] For robustness, we compute also the corresponding marginal effects of going from not owning a website to owning one, and the results are presented in Appendix A3. 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.

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. 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.

The comprehensive data collated by the World Bank's Enterprise Surveys Unit allow us not only to 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. Further, 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. 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 some 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. Second, it has been documented that SMEs often lack the funds to continually enhance their technologies

(Strack et al. 2021). 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 some 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 efforts of firms to shift their activities online.

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TABLES

Table 1: Regression Models

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

Notes: Table 1 specifies the econometric models used throughout this paper to estimate the effects on outcome variables of different forms.

1. In all specifications:
   (i) 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.
   (ii) 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 $\mathrm{c_j}$ 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.

Source: Authors.

Table 2: Variable Descriptions and Statistics

Var. Code	Questionnaire (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 because of coronavirus disease (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 because of 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)
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: Labor											
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 because of 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)

Var. Code (1)	Questionnaire (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)
WORK3	Share of workers laid off because of 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)
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 carryout 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)
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)

Var. Code	Questionnaire (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)
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 3 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)
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: Table 2 lists, explains, and provides summary statistics for all variables that are used in this study, together with the corresponding questionnaire codes. The sum of columns (8) and (10) does not necessarily equal the value in column (5) because of 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.

Data sources: All data are provided by the World Bank (2020b), 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		Labor			
Country	GDPPC ($)	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 Republic	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. Russian Federation	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
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

GDPPC = gross domestic product per capita.

Notes: Table 3 presents measures of country-specific firm performance during the coronavirus disease (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 because of COVID-19, experienced sales decrease, were out of business for more than half the time since 2020 began, 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%. Labor 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 or (ii) laid-off or (iii) furloughed.

Source: World Bank Enterprise Surveys, http://www.enterprisesurveys.org.

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

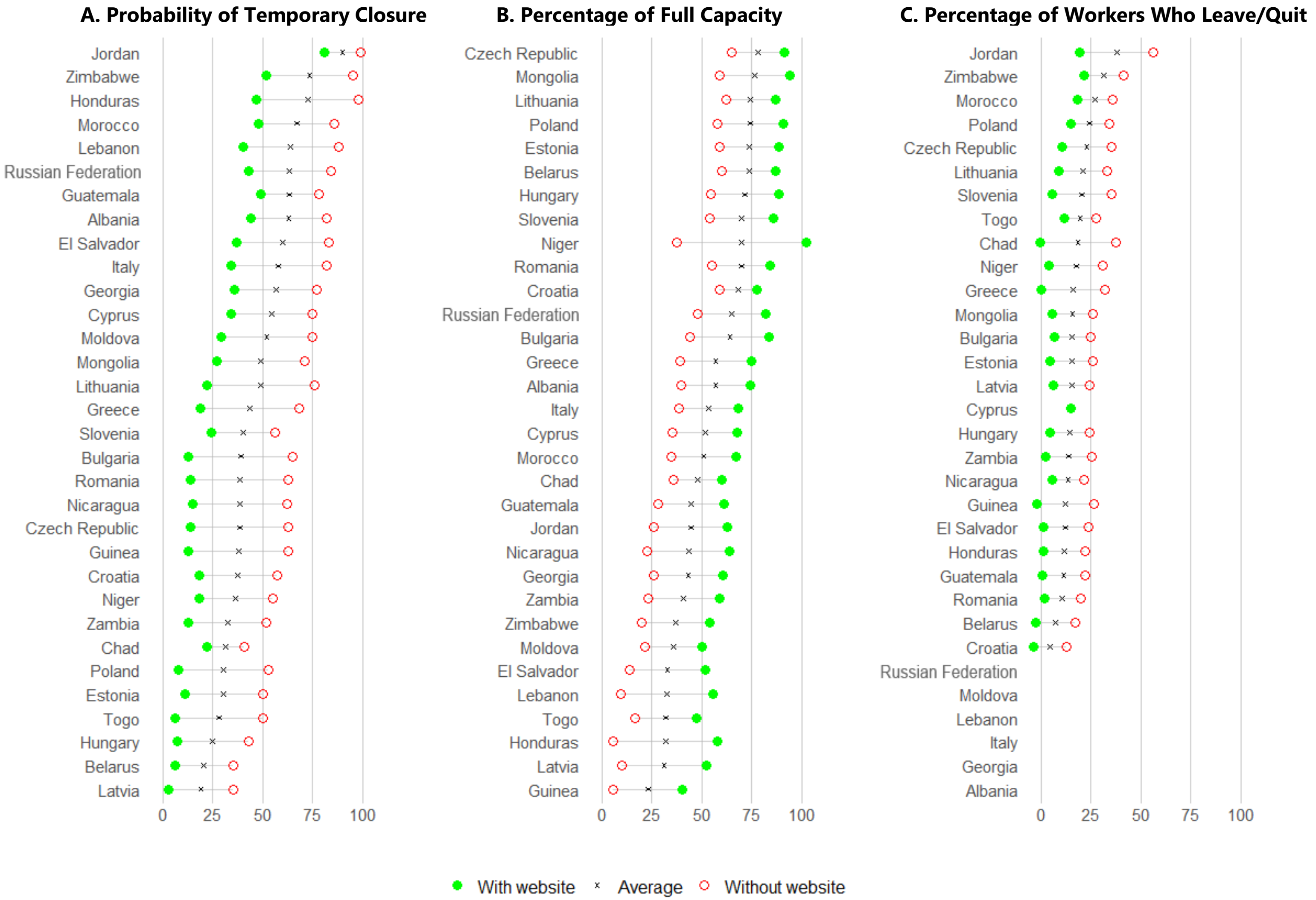
Dependent Variable				Model	Marginal Effect			
					Website Ownership		Online Business	Remote Working
	Question		ID		Non-IV	IV	IV	IV
	(1)		(2)	(3)	(4)	(5)	(6)	(7)
Probability of …	Permanent closure		SALE1	Ordered probit	-2.70***	-2.88***		
					(0.48)	(0.65)		
	Temporary closure				-3.50***	-3.69***		
					(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)	
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)
Because of coronavirus disease (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 [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. Table 2 provides variable definitions and section III includes 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. Detailed results are provided in Appendix A2.

Source: Authors' calculations.

FIGURES

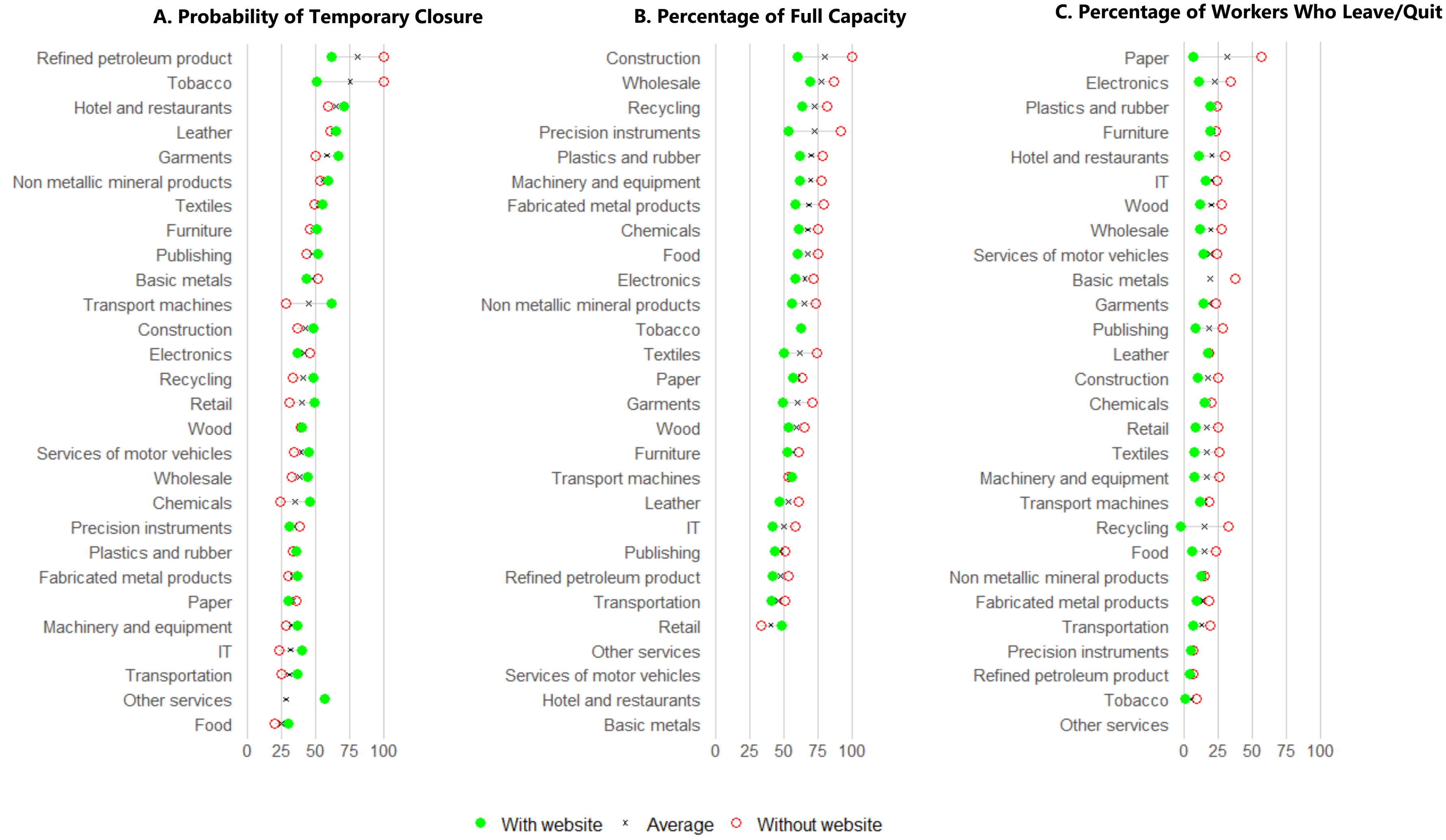
Figure 1: Quantifying the Digital Divide in the COVID-19 Era: Predicted Country Outcomes Conditioned on Website Ownership



Notes: For each country, Figure 1 presents predicted values of three selected coronavirus disease (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).

Source: Authors' calculations.

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



Notes: For each industry, Figure 2 presents predicted values of three selected coronavirus disease (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).

Source: Authors' calculations.

Digital Divide Decoded

Can E-Commerce and Remote Workforces Enhance Enterprise Resilience in the COVID-19 Era?

Using a sample of more than 12,000 firms in 32 countries, the authors empirically examine the impact of digital technology on resilience during the coronavirus disease (COVID-19) pandemic. After controlling for firm characteristics, macroeconomic conditions, and pandemic prevalence, they find that digital technology had a significant and positive effect on firm performance during the pandemic. The evidence suggests that key channels of resilience are electronic commerce and remote work.

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