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Digital Payments and the COVID-19 Shock

The Role of Preexisting Conditions in Banking, Infrastructure, Human Capabilities, and Digital Regulation

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Abstract

Treating data collected pre- and post-COVID-19 as a quasi-experiment, this paper examines the importance of presumed enablers and safeguards in driving the observed expansion of digital payments and digital financial inclusion. The analysis interacts drivers of digital payment usage with a country-specific proxy of the severity of the COVID-19 shock, leveraging variation in both the drivers and the quasi-treatment (the COVID-19 shock) to identify the parameters. Although regulation of banks and digital economic activity were correlated with digital payments before and during the pandemic, the capabilities of users and connectivity (to electricity, the internet, and mobile telephony) were responsible for increased use of digital financial services in response to the shock. An interpretation is that governments and the private sector were able to overcome underdeveloped banking systems and weak regulation of the digital economy, but only where there was adequate digital infrastructure, connectivity, and a high share of the population that understood and could make use of digital payments.

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1. *Introduction*

The COVID-19 pandemic was a shock that provided impetus for increased usage of digital payment services, and perhaps spurred deeper financial inclusion. In fact, between 2017 and 2021, the share of adults reporting having used the internet to make or receive digital payments in the previous year rose, on average, by 7.7 percentage points. However, the standard deviation of these changes is also high, at 8.5 percentage points, indicating substantial variation across countries. Because it was unanticipated and because countries had differing responses in terms of increased use of digital payments, the episode provides an opportunity to identify the drivers of digital payments and digital financial inclusion. Using the 2021 round of the Global Findex survey and other new datasets describing bank regulation and supervision and legal and regulatory enablers and safeguards for digital commerce and (personal) data sharing, we measure the influence on digital payments of dimensions that have not been quantified well to date, while also measuring the influence of drivers such as human capabilities (educational attainment), infrastructure (electricity, internet usage), and the usage of mobile phones.

The literature on the effects of digital payments, and digital financial services (DFS) in general, is growing and surveys of it were available prior to the COVID-19 pandemic (Karlan et al., 2016; Abbasi and Weigand, 2017) and in the context of the pandemic (Agur et al., 2020). Key themes that emerge from the literature on impact evaluation, much of which is focused on field experiments (i.e., randomized controlled trials or 'RCTs') are that: (1) digital payments and transfers can strengthen informal risk-sharing networks, providing a source of resilience to unanticipated shocks that can contribute to higher household savings and consumption (Lee et al., 2021; Jack and Suri, 2011, 2014, 2016; Suri et al., 2012); (2) digital systems are proving a cost effective and secure method for governments to disburse funds to citizens in multiple contexts

(Aker et al., 2016; Banerjee et al., 2015) and for private firms to pay their workers (Breza, Kanz, and Klapper, 2020; Blumenstock, Callen, and Ghani, 2018; Blumenstock et al., 2015);[1] and (3) DFS also hold promise for delivery of savings and credit products (Karlan et al., 2016), though evidence on non-digital delivery mechanisms indicates that commitment devices and/or prompts that guide clients in their financial decision-making may be required to spur household savings (Ashraf et al., 2010; Dupas and Robinson, 2013; Beaman et al., 2014; Dupas et al., 2018; Prina, 2015; Brune et al., 2016) and the experimental evidence has not shown substantial impacts of microcredit on household income, consumption, or entrepreneurial activities (Banerjee, Karlan, and Zinman, 2015).

A small but growing literature has examined the effects of DFS on firm growth and profitability using non-experimental empirical methods, though research prior to the pandemic focused on DFS provision through banks to the exclusion of mobile network operators and fintech firms and tended to cover a limited range of issues (Abbasi and Weigand, 2017).[2] During the pandemic, greater emphasis was placed on DFS as a quick, effective way for governments to disburse funds to those in need and for households and firms to access online payments and financing. World Bank (2022) reports that many developing countries were able to use digital cash transfers during the pandemic to mitigate the adverse distributional effects on poverty. As one example, they note that Brazil remarkably managed to reduce poverty, in part through targeted digital cash transfers, even in the presence of economic contraction. Similarly, helped by digital

[1] Recipients of digital wage payments in Bangladesh and Afghanistan also saved more than those who received wages in cash, likely due to greater security and privacy that digital wage payments provide, especially to women (Breza, Kanz, and Klapper, 2020; Blumenstock, Callen, and Ghani, 2018). And there is some evidence suggesting that receiving digital payments can provide an onramp for recipients to learn how to better use DFS in general. For example, in Bangladesh, factory workers who received their wages directly into an account also learned to use their account without assistance and to avoid illicit withdrawal fees (Breza, Kanz, and Klapper, 2020).

[2] Abassi and Weigand (2017) note that "newer researchers [in this area] often ignore past literature and investigate the same issues."

transfers, India was able to provide aid during the pandemic that reached the majority of urban and rural households. Despite documented successes, observers have cautioned against rapid scaling up of DFS without adequate regulations and safeguards and have acknowledged the potential for DFS to increase inequality (Agur et al., 2020).

Regarding the drivers of DFS prior to COVID-19, evidence from smaller samples of countries than the one used here indicates that multiple factors were at work.[3] Focusing on digital credit provided by fintech firms for a sample of 61 countries, Claessens et al. (2018) find that fintech credit volumes were increasing with per capita income and declining with the competitiveness of the banking sector, presumably because fintech firms found it harder to compete with banks. Fintech credit volumes also declined with the stringency of banking regulation, perhaps because "fintech regulations are also more liberal in jurisdictions where banking regulation is more liberal," or because new lending activities may be harder to undertake in countries with strict prudential and bank licensing regimes.[4] For a sample of 52 countries in 2014 and 2017, Sahay et al. (2020) find that the prevalence of digital payments was positively linked to GDP growth. Based on the existing literature and interviews with policy makers, regulators, fintech companies, and banks, those authors also posit that the safe development of digital financial inclusion is influenced by the financial/digital literacy of DFS users and regulations and digital systems that instill trust through digital identification, consumer protection,

[3] Efforts to identify the drivers of financial inclusion more broadly were forerunners of these more recent studies on drivers of DFS. For example, Rojas-Suárez (2016) and Rojas-Suárez and Amado (2014) show that poor institutional quality (as reflected in weak rule of law and a lack of reliable contract enforcement) and uncompetitive banking sectors were associated with less financial inclusion in Latin America (measured as owning an account at a formal financial institution). Using Global Findex data for 2011 and 2014, Dabla-Norris et al., (2015a,b) also find financial inclusion to be positively linked to per capita income, rule of law, and competition in banking. Similarly, using Findex data from 2014, Deléchat et al. (2018) show that individuals were more likely to be financially included in countries with high levels of per capita income and general financial development.

[4] Claessens et al. (2018), p. 38.

and cybersecurity.[5] We attempt to control for the factors from these studies in the regressions presented below.

A smaller literature explores the drivers of DFS growth during the COVID-19 pandemic itself. Based on a household survey in India, those who switched to using digital payments during the lockdown were significantly more likely to be aware of digital payments modes, more highly educated, and with access to smartphones and debit cards (Saroy et al., 2022). These are similar to characteristics of DFS users in studies prior to the pandemic who were found to be richer (Cohen and Rysman, 2013; Fujiki and Nakashami, 2019), better educated (Koulayev et al., 2016), and more aware of digital payments and generally more financially literate (Wyman, 2017).[6]

Other drivers of DFS adoption differed across the pre-pandemic and pandemic periods. For example, and perhaps not surprisingly, the increase in digital payments during the pandemic depended on social distancing norms and containment measures (De' et al., 2020, Alber and Dabour, 2020). While studies that predated the pandemic found that younger respondents were more likely to be DFS users, Saroy et al. (2022) found that during the pandemic middle-aged survey respondents in India were the most likely to have become DFS users, and that many of them had earlier tried but subsequently abandoned digital payments. Similarly, Jonker et al. (2022) found that digital payments increased more sharply during the pandemic for older age groups, which had typically been slower to adopt DFS.

[5] On approaches to regulating DFS, see Staschen and Meagher (2018), Gutierrez and Singh (2013), and Tarazi and Breloff (2010). Gutierrez and Singh (2013) also provide evidence of a positive association between mobile money usage and aspects of the regulatory regime related to e-contracting, consumer protection, and interoperability, among other factors, for a sample of thirty-five countries. On the benefits of digital identification systems, and biometric identification in particular, in contexts where human capabilities (illiteracy and low levels of financial/digital literacy) constrain financial inclusion, see Muralidharan, Niehaus, and Sukhtankar (2016).

[6] Individual education and income were also significantly associated with broader measures of financial inclusion in studies that used Findex data (see, e.g., Allen et al., 2016; Deléchat et al., 2018).

This demographic shift in DFS usage was furthered by government programs to transfer cash to support struggling households during the pandemic. For example, those dependent on India's Direct Benefit Transfer (DBT)-based income support programs were compelled to use DFS to access their entitlements (Saroy et al., 2022). More generally, Gentilini et al. (2020) report that nearly 17% of the world's population was covered by at least one government COVID-19-related digital cash transfer scheme in 2020-2021. Because governments needed to deposit these transfers into a formal account, increased use of digital payments was also associated with the presence of formal financial institutions. In the Indian context, for example, proximity to brick-and-mortar banking establishments was significantly linked to digital payment adoption during the pandemic (Saroy, 2022). And the Findex 2021 data reveal that 39 percent of adults in developing economies opened their first financial account for the purpose of receiving a direct government payment (such as a wage or benefit payment) or a wage payment from a private-sector employer, and that most of those accounts were with brick-and-mortar financial institutions (Demirguc-Kunt et al., 2022). Finally, there is also evidence that the pandemic-induced increase in use of digital payments persisted after the initial waves of COVID-19 had subsided (Jonker et al., 2022; Ardizzi et al., 2020).

Despite the proliferation of studies on the role of digital payments during COVID-19, what has been lacking is systematic global data on drivers of DFS usage and, until the release of the 2021 Global Findex data, on DFS usage itself during the pandemic, and accompanying empirical analysis to measure the relative impacts of those drivers.[7] This paper is an attempt to begin filling this research gap. We first establish the wide variation across countries during the COVID-19 period in the increase in digital payments and usage of digital financial services. Our

[7] Sahay et al. (2020) note that, "to the best of our knowledge, there are no comprehensive global studies on fintech and financial inclusion, reflecting in part the limited availability of cross-country data."

estimation approach is then predicated on the assumption that the shock was unanticipated and that its effects on digital participation depended heavily on conditions on the eve of the pandemic on the dimensions mentioned above – banking development and activity restrictions, legal and regulatory enablers and safeguards for digital commerce and data sharing, human capabilities of DFS users, infrastructure development, and mobile phone usage.

We find that banking sector development and legal and regulatory enablers and safeguards for participation in the digital economy are associated with digital payment usage. However, these factors are strongly correlated with the level of DFS usage in both 2017 and 2021, rather than with the change in DFS usage during the COVID-19 period, and the association with banking sector development is significantly weaker in countries where regulations on banks' activities are more restrictive. By contrast, proxies for infrastructure and connectivity (for example, the share of the population with access to electricity) and mobile phone usage are both correlated with the increase in DFS usage during the pandemic, and less strongly associated with the level of DFS usage before or after the pandemic (i.e., in 2017 or 2021). Human capabilities as proxied by mean years of schooling are strongly associated with the level of DFS usage (in 2017 and 2021), but also significantly correlated with the change in DFS usage during the pandemic. Similarly, the share of population that uses the internet, which is likely reflective of both connectivity and human capabilities, is significantly linked to both the pre- and post-pandemic levels of DFS usage and to the increase in DFS usage during the pandemic.

Because the COVID-19 shock was unanticipated, we view the factors that are significantly correlated with the change in DFS usage as more likely to summarize causal relationships than those more strongly associated with pre- and post-pandemic levels of DFS usage. However, and at the risk of reading too much into our estimates, the patterns suggest that longer-run development of banking and the legal and regulatory environment for digital economic activity have been important contributors to DFS usage, but that the factors most closely related to the capabilities of users and connectivity (to electricity, the internet, and mobile telephony) were primarily responsible for increasing DFS usage because of the COVID-19 shock. One interpretation is that governments and the private sector were able to work around underdeveloped banking systems, and poor laws and regulations of the digital economy, but only if there was an adequate level of digital infrastructure and connectivity and a high share of the population that understood and could make use of digital payments. We return to this discussion later in the paper.

The rest of the paper is organized as follows. Section 2 describes the data sources for DFS usage and its drivers and the specific variables that we use in the empirical analysis. Section 3 describes our estimation approach in greater detail, while section 4 summarizes our empirical results. Section 5 discusses the empirical patterns that we find and potential policy implications. Section 6 offers concluding remarks and lays out potential directions for future research.

2. Data

For the empirical analysis, we rely on country-level datasets with wide global coverage that summarize DFS usage, banking regulation, human capital development, and regulation of digital commercial activity and data sharing. In this section, we briefly describe the sources of those data and the specific variables that we rely on from each source.

Global Findex Database

The Findex database provides information on how adults around the world use financial services, from payments to saving and borrowing, and how they manage financial events.[8] The

[8] For details on Findex, including links to the data and questionnaires, and documentation on methodology, see https://www.worldbank.org/en/publication/globalfindex/Data.

most recent edition was completed in 2021 for 123 economies (Demirguc-Kunt et al., 2022). It includes indicators of access to and use of formal and informal financial services that have been collected in previous editions of Findex, as well as indicators of the use of cards, mobile phones, and the internet to make and receive payments, including digital merchant payments and payments from the government. In addition to wider country coverage than other data sources, the key advantage of the Findex dataset is that it provides nationally representative demand-side indicators of DFS usage. In contrast, studies that have used supply-side indicators not only have used data for a smaller sample of countries (in which advanced economies were more heavily represented), but also relied on indicators for a subset of DFS providers. For example, Claessens et al. (2018) rely on data collected from surveys of fintech platforms and other public sources by the Cambridge Center for Alternative Finance (CCAF) that explicitly excludes digital credit provided by commercial banks, focuses on the larger fintech platforms, and excludes other providers of digital credit such as online mortgage lenders, big tech firms, and e-commerce platforms.[9]

In the empirical analysis that follows, the dependent variable indicates the share of the adult population in a country that made or received a digital payment in 2020-2021 using any type of provider (see Table 1 for a detailed variable description).

Bank Regulation and Supervision Survey Dataset

The Bank Regulation and Supervision Survey (BRSS), collected by the World Bank Group, provides comparable economy-level data on how banks are regulated and supervised around the world. The most recent edition was completed for 160 jurisdictions in 2019 (Anginer et al., 2022; World Bank, 2019).[10] In the analysis that follows, the BRSS indicator is the index of overall restrictions on banking activities. Following Barth, Caprio, and Levine (2013), it is

[9] See Claessens et al. (2018), p. 31, Box A.
[10] For more details on the survey itself and the BRSS dataset, see: https://www.worldbank.org/en/research/brief/BRSS.

computed using questions that capture the degree of stringency of banking regulation in engaging in securities, insurance, real estate, and nonfinancial business activities. The index ranges between 3 and 12, with higher values indicating stricter regulation.

Global Data Regulation Dataset

Produced as part of World Bank (2021), the Global Data Regulation Diagnostic summarizes the laws and regulations concerning key aspects of a data economy for 80 countries. Following Chen (2021), the empirical analysis below relies on an index of enablers that facilitate use/reuse of data and another index of safeguards that protect the rights of market players in the data economy. The enablers index covers three dimensions: e-commerce, data produced for public purposes (e.g., public policy), and data collected by the private sector for business purposes. The safeguards index covers four dimensions: personal data, nonpersonal data, cybersecurity, and cross-border data. The indexes range from 1 to 17 with higher values indicating that a country has more of the regulations that enable data use/reuse,[11] or safeguard against its misuse. Index scores are aggregated across survey responses. For example, countries received one point if they had a law or regulation that explicitly governs e-commerce/e-transactions. The full list of the survey questions used to score countries is found in Annex 2 of Chen (2021).

Human Development Index

Collected as part of UNDP (2022), the Human Development Index (HDI) is a summary measure of average achievement on three key dimensions of human development: a long and healthy life, being knowledgeable, and having a decent standard of living.[12] The health dimension is measured using life expectancy at birth; knowledge using expected years of schooling and mean

[11] However, the highest possible value on the enablers index is 16.
[12] UNDP (2022). Data available at: https://hdr.undp.org/data-center/documentation-and-downloads.

years of schooling; and living standards are summarized by gross national income per capita. Because the knowledge dimension is the most relevant aspect of human capabilities for using DFS, we rely only on mean years of schooling among adults as an explanatory variable in the regressions presented below. However, the empirical findings are qualitatively similar if we use the full HDI as our explanatory variable summarizing human capabilities, or if we replace the HDI with the Human Capital Index described in World Bank (2020).

World Development Indicators

The explanatory variables that we use to describe connectivity (share of population with access to electricity, that uses the internet, or has a mobile cellular subscription) are taken from *World Development Indicators* (WDI), as are controls for growth in GDP per capita, inflation, and population. More detailed descriptions of the variables used in the analysis are found in Table 1.

3. *Estimation Approach*

Our estimation approach is designed to reduce omitted variable bias and endogeneity bias. By focusing on digital payments in 2021, well after the initial shock of COVID-19, we argue that the estimated parameters for the explanatory variables will suffer less from endogeneity bias than a model in which digital payments and the explanatory variables are contemporaneous. More specifically, serial correlation is likely in a cross-country model of digital payments based on factors such as regulatory enablers, digital infrastructure and human capabilities, but explaining variation in digital payments after experiencing the unexpected COVID-19 shock should reduce concerns about this sort of bias. To address omitted variable bias, we estimate the level of digital payments in 2021 both with and without a control for the level of digital payments in 2017, the last pre-pandemic year for which we have digital payments data. In the model that controls for the level in 2017, we are essentially modelling the change in the level of digital payments during the pandemic. Presumably there are many unobservable, time-invariant variables (that is, invariant over the time frame we are examining), that explain digital payments. By including the level of digital payments just prior to the pandemic, we control for these time-invariant unobservable determinants of digital payments in 2021.

Equation 1 relates the share of the adult population that made or received a digital payment in country *i* in 2021 ($DigPay_{i2021}$) to the factors described above. We include the trend in digital payment usage, measured as the change in the share of the adult population that made or received a digital payment in 2017 versus 2014, to capture the baseline trend in DFS adoption in a country prior to the pandemic.[13] X_{i2019} represents controls for GDP per capita, inflation, and country population. We expect GDP per capita to be positively linked to digital payment usage (and other DFS variables); we do not have strong priors about the links between DFS variables and inflation and population.

$$\begin{aligned} DigPay_{i,2021} = \alpha + \beta_1 \Delta DigPay_{i,2014-2017} + \boldsymbol{\beta_2} X_{i,2019} + \boldsymbol{\beta_3} Banking_{i,2019} \\ + \boldsymbol{\beta_4} Infrastructure_{i,2019} + \beta_5 Mobile\ phones_{i,2019} \\ + \boldsymbol{\beta_6} Digital\ Regulation_{i,2019} + \beta_7 Capabilities_{i,2019} + \varepsilon_i \end{aligned} \quad (1)$$

The explanatory variables of most interest in equation 1 relate to banking sector development, infrastructure and connectivity, human capabilities as reflected in years of education, mobile phone usage and regulation of the digital economy. Regarding banking, some observers have expressed concern that lightly regulated digital lending could not only pose harm to less sophisticated borrowers, but also threaten financial stability if enough users lose trust in digital

[13] In using the 2017 data as the best available estimate of digital payment usage just prior to the pandemic, we implicitly assume that either digital payment usage evolved very slowly in 2018-2019, the years just prior to the outbreak of COVID-19, or that the coefficient on the 2014-17 digital payments trend variable that is also included in the model adequately captures the changes in 2018-19.

financial technologies (Sahay et al., 2020). While we cannot test this directly because we lack a measure of regulation of DFS, particularly digital lending, for a wide enough sample of countries, we know that banks are the most heavily regulated and supervised financial institutions in most countries, including low- and middle-income countries (hereafter referred to as LMICs; Anginer et al., 2022; World Bank 2019). We also know that banks, when permitted, have become increasingly involved in the provision of DFS, sometimes partnering with Fintech companies (Pazarbasioglu et al., 2020; Sahay et al., 2020). We therefore test a hypothesis related to the idea that light regulation of digital lending may foster instability, namely that banking sector development is associated with development of DFS, and that (overly) restrictive regulations and supervisory practices regarding the range of activities that banks may engage in can impede DFS development. In our regressions, we control for banking assets (as a share of GDP), which should be positively linked to DFS, and an index of restrictions on banks' activities from the BRSS, which should be negatively linked to DFS indicators (as described above).

$Infrastructure_{i,2019}$ represents two variables that describe the quality of digital infrastructure and the level of connectivity in a country, namely the share of the population with access to electricity and the share that uses the internet. We also control for the number of mobile cellular subscriptions (per 100 residents) since DFS are increasingly used via mobile phones. We expect that digital payment usage is positively linked to all three of these connectivity variables (access to electricity, usage of internet, and prevalence of mobile cellular subscriptions).

$Digital\ Regulation_{i,2019}$ represents the two indexes compiled from the World Bank Global Data Regulation Diagnostic described above – the index of enablers that facilitate use/reuse of data and the index of safeguards that protect the rights of market players in the data economy. We expect that at least the latter indicator will be positively associated with digital payment usage because privacy protections tend to help build trust in digital transactions. The former variable's effect is ambiguous, at least in the short run. On the one hand, such laws require that digital signatures have equal recognition under the law as properly signed paper contracts. On the other hand, such regulations require authentication procedures to ensure that parties involved in a transaction are real, which can deter the use of digital payments in contexts where authentication comes at the expense of privacy rights.[14]

Finally, $Capabilities_{i2019}$ is included to control for human capabilities that are positively linked to DFS usage as reflected in educational attainment. In the regressions below, we rely on mean years of schooling among adults aged 25 or older from the UNDP's Human Development Index to proxy for this factor, because of its wide country coverage. Again, results are qualitatively similar when the schooling variable is replaced by the full HDI or the World Bank Human Capital Index.

Equation 2 adds to equation 1 the share of the of the population that made or received a digital payment in 2017 ($DigPay_{i,2017}$), which is from the penultimate version of the Global Findex dataset. It is included to control for the level of digital payment usage in a country prior to the pandemic.[15] Recall that our estimation approach for uncovering causal relationships is rooted in the assumption that the COVID-19 shock was unanticipated, and that its effects on digital participation depended on pre-existing conditions. For this reason, the explanatory variables are measured in 2019 to the extent possible. By controlling for the level of digital payment usage just prior to COVID-19 (and the trend in payment usage prior to that), equation 2 fully controls for developments in payment usage to that point. For these reasons, the coefficients for the remaining

[14] For additional details on the construction of these indexes, see World Bank (2021, Chapter 6).
[15] Note that the Findex data were not collected in 2018 or 2019, so 2017 is the last date prior to the pandemic for which indicators of DFS usage are available for a wide sample of countries via Findex.

explanatory variables represent our cleanest attempt to identify the causal effects of the drivers described above on changes in digital payment usage during the pandemic.

$$DigPay_{i,2021} = \alpha + \beta_1 DigPay_{i,2017} + \beta_2 \Delta DigPay_{i,2014-2017} + \boldsymbol{\beta_3} X_{i,2019} + \boldsymbol{\beta_4} Banking_{i,2019} + \boldsymbol{\beta_5} Infrastructure_{i,2019} + \beta_6 Mobile\ phones_{i,2019} + \boldsymbol{\beta_7} Digital\ Regulation_{i,2019} + \beta_8 Capabilities_{i,2019} + \varepsilon_i \quad (2)$$

The foregoing discussion, however, does not imply that estimates from equation 1 are of little value. While they cannot be used to reliably identify the causal impact of drivers prior to the pandemic (because those variables could be endogenous to the evolution of digital financial usage), comparing them to the estimates from equation 2 provides a method for distinguishing factors that were correlated with DFS adoption over the extended period prior to the pandemic from those that were causally linked to DFS adoption during the shorter COVID-19 period. We return to this discussion below after presenting the regression results.

4. Empirical Results

Multiple patterns emerge from the correlations between the variables used in the regressions that appear in Table 2, panel B. First, banking sector development is significantly correlated with the payments variables. For example, the correlation between banking assets/GDP and the population share that made or received a digital payment is 0.53. Similarly, the index of restrictions on banks' activities is negatively correlated with the digital payment usage. These patterns provide initial evidence consistent with the proposition that banks have positively affected DFS usage, and that tight restrictions on their activities may have curtailed increases in DFS usage in some countries.

Second, the other potential drivers related to infrastructure and connectivity, mobile phone usage, user capabilities as reflected in years of schooling, and regulation of the digital economy are also significantly correlated with the digital payment usage, suggesting they are good candidates to be included as explanatory variables in our regressions. At the same time, those variables are also correlated with each other – for example, the correlation between mean years of schooling and the share of the population that uses the internet is 0.86, while that between the index of regulatory enablers of the digital economy and years of schooling is 0.35. This suggests that countries have made progress on multiple dimensions that support DFS adoption at the same time, which could pose challenges for identifying separately the effect of each of these drivers in our regressions.

a. Main regression results

In Table 3, the dependent variable in the regressions is the share of the population aged 15 or older that made or received a digital payment in 2020-1. Column (1) begins by including on the right-hand side of the regression the trend in digital payment usage from 2014 to 2017, and the banking variables. The coefficient for banking assets/GDP is positive, while that for the index of restrictions on banking activities is negative. Macro controls are added in column 2; and the coefficients for the banking variables remain very similar to those in column 1.

Because of the limited degrees of freedom in these cross-country regressions, and the collinearity between some explanatory variables described above, we add the variables for capabilities of users, infrastructure and connectivity, and regulation of the of the digital economy one at a time.[16] Column (3) shows that the capabilities measure, mean years of schooling, is

[16] Since we cannot incorporate all explanatory variables in a single model due to our limited number of observations and given the aforementioned collinearity between some of those variables, we acknowledge that the coefficient for the added variable in models 3-8 may suffer from some omitted variable bias. Nonetheless, as discussed further below,

positively correlated with digital payment usage. The share of population with access to electricity is also positively linked to digital payment usage (in column 4), though the coefficient is less significant than for the schooling measure. The population share that used the internet prior to the COVID-19 shock is also positively associated with digital payment usage (in column 5). The prevalence of mobile cellular subscriptions is not, however, significantly linked to digital payment usage (column 6). Note that while the banking variables remain significant across the first six specifications (with one exception for the activity restrictions variable), they are smaller in magnitude when either the years of schooling or internet usage variables is added to the regression.

In columns 7-9, we introduce the variables that measure regulation of the digital economy. Note that this reduces the sample size to 44 countries. Still, the index of digital enablers is significantly linked to digital payment usage (in column 7), as is the index of safeguards (in column 8). The banking assets variable remains positively correlated with digital payments when the indexes of digital regulation are included in the regression, though the coefficient on the index of restrictions on banks' activities becomes small in absolute value and of opposite sign in columns 7 and 8.

Overall, Table 3 shows strong statistical associations between digital payment usage and the level of banking development, human capital as reflected in schooling, infrastructure and connectivity, and regulation of the digital economy. These relationships provide empirical support for many of the themes emphasized in World Bank (2021), the first such evidence that controls for these factors within the same models and for a wide set of countries. We present results for the sample of countries that have data for the full set of explanatory variables, but we note that very

we can compare the magnitude of those coefficients to assess relative strength of each variable as a predictor of digital payments.

similar qualitative results hold when we use the maximum number of available countries for each regression in Table 3.[17]

Table 4 presents estimates of equation 2, which adds the pre-COVID-19 level of digital payment usage to the models in Table 3. For the reasons above, we view these as better estimates of causal relationships between the 'drivers' variables and the increase in digital payment usage during the pandemic. Not surprisingly, the level of pre-COVID-19 digital payment usage in 2017 is strongly linked to the 2020-1 digital payment usage levels, thus indicating a high level of persistence in digital payment usage with the coefficient on the lagged dependent variable hovering around 0.9 in all specifications. The estimated coefficients for the banking variables and the digital regulation variables are much smaller in magnitude in Table 4 than in the static model specifications reported in Table 3. However, DFS user capabilities as reflected in years of schooling and internet usage (which is also reflective of infrastructure and connectivity) remain strongly statistically linked to digital payment usage. Access to electricity is also linked to digital payment usage, though the statistical relationship is weaker. Unlike the models in Table 3, there is also a strong relationship between the prevalence of mobile cellular subscriptions and digital payment usage, consistent with the notion that mobile phones were crucial for sending and receiving money digitally during the pandemic. Finally, country population is significantly linked to digital payments in all models in Table 4, indicating that residents of more populous countries were more likely to increase digital payment usage during the pandemic. The pattern could be attributable to government initiatives or private initiatives, or both, in populous countries.

[17] There are 83 countries that have data for all variables used in models 1-6; 44 countries for all variables used in models 7-9. Results that include the maximum number of countries for each individual specification are available from the authors by request.

Our findings are consistent with the interpretation that the COVID-19 shock increased digital payments and that this increase was large enough to parse out which enablers most affected this change. Because the COVID-19 shock was unexpected, our approach assumes that pre-determined country-level variables can be used to identify causal effects on the change in digital payments. To this point, however, the analysis has not explicitly accounted for the relative severity of the COVID-19 shock across countries. To further support the interpretation that the correlation between the enablers and digital payments may reflect a causal link, Table 5 therefore examines whether the effect of the enablers on digital payments is larger in those countries where the economic impact of COVID-19 was greater. We follow Mahler et al. (2020) and construct a proxy for the intensity of the economic impact of COVID-19 on each country, measured as the difference between two growth forecasts for 2020. The first forecast was produced in January 2020 and did not account for the impact of COVID-19 (World Bank 2020a); the second forecast is from June 2020 which did account for the economic effects of COVID-19 (World Bank 2020b). The advantages of this approach are two-fold: first, it accounts not only for the unexpected COVID-19 shock but also its magnitude, which improves the precision of our estimates, and second, the magnitude is a country-specific change in expectations which is, by construction, not collinear with time-invariant country level effects, further allaying concerns about endogeneity.

The results reported in Table 5 indicate that the coefficients for the interactions between the enablers and the COVID-19 shock are positive for all explanatory variables. When we trace out the nonlinear marginal effect of educational attainment, it is positive over the entire range of COVID-19 shocks, although the effects are estimated with notable uncertainty as proxied by the

90% confidence intervals – see Figure 1.[18] More generally, although not all explanatory variables have statistically significant marginal effects averaged over the observed shocks, the point estimate of the interaction term is positive and statistically significant for each enabler. An interpretation is that, if the shocks had been even larger, each of the enablers would have had a positive effect that was statistically significantly different from zero (at conventional levels) on digital payments. Indeed, for all enablers except the indexes of regulatory enablers and safeguards for the digital economy, the effects were positive and statistically significant over the high end of the observed range of shocks, as shown in Figures 1-6. Moreover, larger confidence intervals, however computed, are expected around the point estimates for the data enablers variables due to the smaller samples used for those estimations.

b. Magnitude of the estimated effects and policy choices

Regarding the magnitudes of the estimated coefficients, Table 6 shows the normalized estimates of the average effects of each of the explanatory variables of interest, namely education, infrastructure (electricity, internet use, and mobile subscriptions), and the data regulation variables (enablers and safeguards). To recap, our argument has been that the estimates from Table 3 could be influenced by omitted variables bias, whereas the results from Table 4 dealt with this concern to some extent by controlling for the pre-COVID-19 level of digital payment usage in 2017. The inclusion of the lagged dependent variable presumably controls for long-run determinants of digital payment usage that might have been correlated with our explanatory variables. Those

[18] See Imbens (2021) for a discussion of why confidence intervals and p-values are not reliable metrics for making inferences about the magnitude of econometric estimates and particularly for making arguments about policy choices, which is a key objective of this paper. A key reason is that computing proper confidence intervals requires knowledge about the distributional properties of the data generation process underlying the estimation sample. If the distribution is not normally distributed, then the confidence intervals computed by standard statistical packages are unreliable. Another reason is that for policy discussions, if one policy choice is estimated to have a much larger average effect than an alternative policy, it is unclear that the proper way of computing the uncertainty around the average effect is the test for the null hypothesis that the impact is zero at an ad-hoc threshold level of statistical significance.

results come from the estimation of equation 2, which we call the dynamic specification of the model. Lastly, the results presented in Table 5 relied on the interaction between the size of the COVID-19 shock and each explanatory variable for the identification of the effect of each on the use of digital payments in 2021, while also controlling for the lagged dependent variable (as of 2017). Since the size of the COVID-19 shock was unexpected, driven by changes in growth expectations in a short six-month period (as explained earlier), our claim is that those estimates are closer to being unbiased than the other two approaches.

In fact, the results presented in Table 6 indicate that the magnitudes of the average effects of the explanatory variables do vary systematically across the three columns. The results in the first column, drawn from the static model, have notably larger effects than the results from the dynamic models presented in columns 2 and 3 in Table 6. The results also change in terms of the rankings of the magnitudes across the explanatory variables between columns 2 and 3, thus suggesting that the average effect is different when estimated with the dynamic models with and without interactions. Furthermore, it is worth noting that the range of the models' adjusted R-squares are much higher in the dynamic models than in the static models, indicating a better goodness of fit.

Specifically, in Table 6, column 1, the estimated effect of a one standard deviation shock to schooling supposedly leads to an almost 16 percentage point (p.p.) increase in the share of adults using digital payments in 2021. In contrast, in columns 2 and 3 this effect falls substantially to 3.1 p.p. in the dynamic model without interactions and to 2.6 p.p. in the model with the relevant interaction. Similarly, the estimated impact of a one standard deviation shock in internet use prior to the COVID-19 shock seems to increase digital payments by almost 19 p.p. in column 1, but this estimate declines in the dynamic model to 3.9 p.p., and to 3.7 p.p. in the model with the interaction.

A similar pattern is observed for the data regulation variables. A one standard deviation shock to each of these variables appeared to raise, on average, digital payment usage in the static model by 6.6 p.p. and 8.8 p.p., respectively, for the enablers data regulations and the data safeguards. In sharp contrast, the respective estimates fall to much smaller absolute values, with the estimated impact of the enablers data variables turning negative to about -0.5 p.p. and the impact of the data safeguards regulations falling to about 0.6 p.p. in the dynamic model but rising slightly to 0.9 p.p. in the dynamic model with interactions. Further, the negative impact of data enablers is plausible because this variable captures regulatory restrictions on the use of digital payments, whereas the safeguards data variables capture the effect of regulations that safeguard data privacy, thus enhancing public trust in digital transactions. These considerations add credence to our interpretation of the dynamic model and the model with interactions as producing estimates that are closer to the true causal effects.

Overall, if we put more emphasis on the results from the dynamic models with interactions with the size of the COVID-19 shock, the largest average effects come from the variables related to digital infrastructure, namely pre-COVID-19 internet coverage with a 3.7 p.p. effect and mobile subscriptions per capita with a 3.2 p.p. effect. These are followed by pre-COVID-19 educational attainment with an effect of 2.6 p.p.

5. Discussion

The key findings from the base results in Table 4 and Table 5, which are again our best attempts to uncover causal relationships, center on the importance of infrastructure and connectivity and the capabilities of users in facilitating greater usage of digital payments during the crisis. The patterns underscore the importance of policies that promote widespread access to reliable electricity and access to high-speed broadband signals. Recent research also shows, for example, that the roll-out of 3G internet coverage in developing countries has had beneficial employment effects, especially on the labor force participation rates of women (Chiplunkar and Goldberg, 2022). Our results suggest that better infrastructure and internet coverage can also facilitate receipt of digital payments, which are more convenient and reliable for recipients, and spur digital commerce by making electronic payment options available.

At the same time, World Bank (2021) shows that a large share of the residents of LMICs who do not use the internet actually live within range of a broadband signal. Part of the reason for these usage gaps is that mobile phones and data packages are not affordable to them, so policies to increase competition on those dimensions could be beneficial in many contexts. Another part of the story emphasized in World Bank (2021), however, is that internet usage gaps stem also from the large share of the population in many countries that lacks digital literacy (and financial experience and capabilities). Here we provide the first global evidence showing that the capabilities of users, as reflected in years of schooling and internet usage rates, explains substantial variation in usage of digital payments, and likely of other DFS. Our findings suggest that policies that improve these capabilities could be crucial for increasing DFS usage and spurring greater financial inclusion.

Banking development and regulations that enable digital commercial activity while safeguarding against harm to participants were not robustly associated with the gains in digital payment usage during the pandemic in the sense that the coefficients tended to be small in magnitude and to change signs across various model specifications. A possible interpretation for those patterns is that countries were able to work around under-developed banking sectors, overly restrictive regulations on banking activities, and weak regulatory frameworks for enabling and safeguarding digital participation, as long as they had invested well in infrastructure for electricity and broadband access and their residents understood how to receive and make digital payments and could see the value in them.

While we believe that this interpretation is plausible, we offer two caveats. First, the need to receive and make digital payments was heightened during the pandemic. As the situation normalizes, pre-pandemic financial behaviors may re-surface thus eroding gains in digital payment usage and DFS usage more broadly. Monitoring whether, and understanding why, gains in DFS usage were temporary or permanent will be an important area for future research. Second, while banking development and digital regulatory frameworks were not associated with the *increase* in digital payments during COVID-19, both were strongly correlated with the *level* of digital payments as shown in the estimates of equation 1 in Table 3 and could be important drivers of DFS in specific contexts. It seems likely that countries that make use of established banking sectors to further deploy DFS, while at the same time developing and tweaking regulatory frameworks to safeguard DFS users from harm, will be positioned to reap more benefit for a wider cross-section of their populations. Our sense, though, is that this will be a longer-term proposition than the rapid gains in digital payments witnessed during the COVID-19 shock.

6. Conclusion

We provide evidence for a wide set of countries on the drivers of digital payments during the COVID-19 pandemic. While banking development and regulation, regulation of digital commercial activity and data sharing, the capabilities of users, and infrastructure and connectivity were all correlated with the prevalence of digital payments prior to the pandemic, user capabilities and infrastructure/connectivity were the drivers of the substantial increases in digital payments during the pandemic. The patterns suggest that policies that improve digital and financial literacy, broadband coverage, and the coverage and reliability of electricity networks are crucial for extending digital payments, and DFS more broadly, to more people thus achieving deeper financial inclusion.

While we have tried to glean as much as we can from the new global data sources used in this paper and offered first evidence for a large set of countries on the importance of hard-to-quantify factors such as user capabilities, there is much more to learn. Other data sources, particularly from households and firms, can shed light on whether and how governments' digital cash transfers during the pandemic have deepened financial inclusion and changed financial behaviors. Although researchers have speculated that digital payments can be a gateway to fuller financial participation (see, e.g., Demirguc-Kunt et al., 2022), rigorous evidence on this is lacking, aside from RCTs that indicate that recipients learn how to take fuller advantage of digital payments over time (see, e.g., Breza, Kanz, and Klapper, 2020). An important area for future research concerns understanding the contexts in which basic DFS improve the lives of population segments that have been under-served by formal financial services providers and how DFS can lead to deeper financial inclusion.

It will also be important to update the data sources relied on here, particularly the Findex data summarizing usage of financial services, but also those summarizing bank regulation and supervision and regulation of digital economic activities. Information on the use of digital financial services by firms may also be important to understand firm financial constraints. Further, it would be beneficial to expand surveys of bank regulation and supervision to encompass their DFS activities. Moreover, there is no comprehensive global data on regulation and supervision of non-bank providers of DFS, nor is there systematic data on the activities and performance of fintech firms throughout the world. Improvements in these types of data will be crucial for understanding the regulatory and economic contexts in which DFS can flourish, while safeguarding the interests of DFS users through consumer protection initiatives and, especially, protection of their personal data.

The Findex survey continues to be an indispensable source of data on usage of financial services throughout the world. Ensuring that future Findex rounds are fielded should be a priority for development practitioners and donors with interest in promoting financial inclusion. By asking the same questions in future rounds, for example on digital merchant payments, Findex data can provide valuable information on trends in DFS usage over time and whether gains in DFS usage during COVID-19 were permanent or transitory. Developing new questions that can better summarize the digital borrowing and saving activities of respondents can offer a more complete picture of the benefits (and risks) of DFS for households. And perhaps the largest value added from additional data work would be to expand the country coverage for all the datasets used in this analysis. While the data sources exploited in this paper have yielded useful insights, our sense is that this is the tip of the iceberg in terms of what researchers will learn about the importance and drivers of DFS for households across the globe.

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Table 1. Variable Description

Variables	Source	Long description
Dependent variables		
Made or received a digital payment (% age 15+)	Global Findex	The percentage of respondents who report using mobile money, a debit or credit card, or a mobile phone to make a payment from an account -or report using the internet to pay bills or to buy something online or in a store--in the past year. This includes respondents who report paying bills, sending or receiving remittances, receiving payments for agricultural products, receiving government transfers, receiving wages, or receiving a public sector pension directly from or into a financial institution account or through a mobile money account in the past year.
Independent variables – banking		
Overall Restrictions on Banking Activities (2016)	BRSS	Level of regulatory restrictions for bank participation in securities activities, insurance, real estate financial activities and nonfinancial businesses. The question on nonfinancial businesses became available in the 4th round of the BRSS.
Banks' assets (% GDP) (2019)	GFDD	Total assets held by deposit money banks as a share of GDP.
Macro controls		
GDP per capita growth (mean over 2015-2019)	WDI	Mean of the annual percentage growth rate of GDP per capita over past five years (including the current one), based on constant local currency.
log(population) (2019)	WDI	Natural logarithm of the total population in a country.
Inflation, consumer prices (annual %) (2019)	WDI	Inflation, consumer prices (annual %).
COVID growth differential (2020)	Global Economic Prospects	Difference between the two growth forecasts for 2020. The first forecast was produced in January 2020 (World Bank 2020a) and the second forecast is from June 2020 World Bank 2020b).
Enablers		
Mean years of schooling (2019)	UNDP	Mean of years of schooling for adults aged 25 years and more.
Access to electricity (% of population) (2019)	WDI	The percentage of population with access to electricity.
Individuals using the Internet (% of population) (2019)	WDI	Individuals who have used the Internet (from any location) in the last 3 months.
Mobile cellular subscriptions (per 100 people) (2019)	WDI	Subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology.
Enablers data economy	Chen (2021)	Score capturing the presence of enablers of the data economy. The higher the score, the more the regulatory environment is fit for the development of a data economy. Data as of 2020.
Safeguards data economy	Chen (2021)	Score capturing the presence of safeguards of the data economy. The higher the score, the more the regulatory environment is fit for the development of a data economy. Data as of 2020.

Table 2. Descriptive statistics

Panel A. Summary statistics

Variables	N	Mean	Sd	Min	Max
Made or received a digital payment (% age 15+)	83	70.929	25.644	17.623	100.000
Overall Restrictions on Banking Activities (2016)	83	6.783	2.031	3.000	12.000
Banks' assets (% GDP) (2019)	83	77.294	44.905	9.697	248.123
GDP per capita growth (mean over 2015-2019)	83	2.484	1.813	-1.409	8.767
log(population) (2019)	83	16.660	1.567	13.130	21.065
Inflation, consumer prices (annual %) (2019)	83	5.525	27.885	-3.233	255.305
COVID growth differential (2020)	83	7.624	2.416	2.807	14.987
Mean years of schooling (2019)	83	9.997	2.947	2.115	14.091
Access to electricity (% of population) (2019)	83	91.327	18.337	18.375	100.000
Individuals using the Internet (% of population) (2019)	83	66.072	24.528	14.700	98.046
Mobile cellular subscriptions (per 100 people) (2019)	83	121.518	30.259	57.366	288.533
Enablers data economy	44	9.002	2.957	3.500	16.000
Safeguards data economy	44	10.185	3.589	1.250	16.464

Panel B. Pairwise correlations

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
Made or received a digital payment	[1]	1												
Overall Restrictions on Banking Activities	[2]	-0.44*	1											
Banks' assets	[3]	0.53*	-0.19*	1										
GDP per capita growth	[4]	-0.01	0.01	-0.13	1									
log(population)	[5]	-0.15	0.19*	0.10	-0.08	1								
Inflation, consumer prices (annual %)	[6]	-0.08	-0.04	-0.18*	-0.18*	0.02	1							
COVID growth differential	[7]	0.36*	-0.29*	0.04	0.02	-0.28*	0.21*	1						
Mean years of schooling	[8]	0.75*	-0.40*	0.39*	0.00	-0.29*	-0.06	0.55*	1					
Access to electricity (% of population)	[9]	0.43*	-0.17	0.44*	0.17	-0.11	-0.27*	0.49*	0.72*	1				
Individuals using the Internet (% of population)	[10]	0.78*	-0.44*	0.54*	-0.03	-0.27*	-0.20*	0.45*	0.86*	0.75*	1			
Mobile cellular subscriptions (per 100 people)	[11]	0.32*	-0.26*	0.49*	0.02	-0.13	-0.13	0.03	0.35*	0.37*	0.39*	1		
Enablers data economy	[12]	0.40*	-0.13	0.32*	0.01	0.34*	-0.02	0.11	0.35*	0.24	0.38*	0.17	1	
Safeguards data economy	[13]	0.33*	-0.41*	-0.05	-0.06	-0.20	-0.13	0.07	0.25	-0.02	0.31*	0.16	0.18	1

Notes: Pearson correlation coefficients. Asterisk indicates coefficient statistically significantly different from zero (p-value < 0.1).

Table 3. Correlates of Digital Payment Prevalence in 2021

DEPENDENT VARIABLE: Share adults making or receiving payments, 2021 EXPLANATORY VARIABLES:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overall Restrictions on Banking Activities (2016)	-4.146***	-3.657***	-2.068**	-3.657***	-1.631	-3.715***	-0.213	0.979
	(1.257)	(1.372)	(0.976)	(1.352)	(1.055)	(1.392)	(2.255)	(2.153)
Made or received a digital payment (% age 15+) (change 2017-2014)	-31.777	-40.239	19.330	-25.521	30.309	-40.042	-5.431	-4.573
	(25.193)	(28.288)	(29.474)	(30.140)	(25.711)	(28.617)	(35.654)	(39.478)
Banks' assets (% GDP) (2019)	0.246***	0.262***	0.156***	0.226***	0.085**	0.271***	0.315***	0.362***
	(0.056)	(0.059)	(0.042)	(0.062)	(0.040)	(0.050)	(0.057)	(0.054)
GDP per capita growth (mean over 2015-2019)		1.181	0.298	0.559	0.476	1.206	-2.593	-2.739
		(1.262)	(1.039)	(1.395)	(0.947)	(1.273)	(1.772)	(2.012)
log(population) (2019)		-2.199	0.688	-1.809	1.149	-2.273	-2.823	-0.769
		(1.497)	(1.069)	(1.476)	(0.995)	(1.508)	(2.389)	(2.295)
Inflation, consumer prices (annual %) (2019)		0.032	-0.006	0.048*	0.073***	0.031	-0.455	-0.373
		(0.030)	(0.027)	(0.028)	(0.024)	(0.031)	(1.077)	(0.805)
Mean years of schooling (2019)			5.423***					
			(0.828)					
Access to electricity (% of population) (2019)				0.243*				
				(0.131)				
Individuals using the Internet (% of population) (2019)					0.768***			
					(0.117)			
Mobile cellular subscriptions (per 100 people) (2019)						-0.027		
						(0.114)		
Enablers data economy (2020)							2.226*	
							(1.130)	
Safeguards data economy (2020)								2.451***
								(0.749)
Constant	82.853***	112.571***	4.748	86.904***	1.256	116.682***	76.409**	23.809
	(8.797)	(23.163)	(22.535)	(25.221)	(20.650)	(27.806)	(32.288)	(42.485)
Observations	83	83	83	83	83	83	44	44
Adjusted R-squared	0.387	0.389	0.624	0.402	0.622	0.382	0.407	0.466

Notes: Parameter estimates are unweighted ordinary least squares treating each country or economy as the unit of observation. Standard error of the estimates, in parentheses, are robust to heteroskedasticity of general form. *, **, *** denote statistical significance at the standard confidence levels of 10%, 5%, and 1%.

Table 4. Drivers of Digital Payment Usage during COVID-19

DEPENDENT VARIABLE: Share adults making or receiving payments, 2021	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXPLANATORY VARIABLES:								
Overall Restrictions on Banking Activities (2016)	0.154	0.075	0.101	0.039	0.201	0.344	-0.702	-0.524
	(0.442)	(0.455)	(0.422)	(0.439)	(0.441)	(0.482)	(0.800)	(0.895)
Made or received a digital payment (% age 15+) (change 2017-2014)	9.681	9.941	17.741	16.181	20.681*	10.278	26.410	27.282
	(11.374)	(11.813)	(10.904)	(10.602)	(11.139)	(10.829)	(19.946)	(18.926)
Made or received a digital payment (% age 15+) (2017)	0.940***	0.956***	0.883***	0.947***	0.880***	0.975***	0.985***	0.962***
	(0.038)	(0.037)	(0.045)	(0.039)	(0.048)	(0.039)	(0.071)	(0.078)
Banks' assets (% GDP) (2019)	0.020	0.013	0.011	-0.002	-0.004	-0.021	0.051	0.057
	(0.018)	(0.017)	(0.017)	(0.018)	(0.019)	(0.021)	(0.035)	(0.035)
GDP per capita growth (mean over 2015-2019)		0.451	0.335	0.174	0.362	0.350	-0.969	-1.041
		(0.505)	(0.466)	(0.494)	(0.452)	(0.478)	(0.862)	(0.812)
log(population) (2019)		0.967*	1.289**	1.114**	1.414***	1.276**	2.138**	2.000*
		(0.498)	(0.524)	(0.515)	(0.531)	(0.511)	(0.924)	(0.989)
Inflation, consumer prices (annual %) (2019)		-0.008	-0.012	-0.000	0.004	-0.005	-0.377	-0.346
		(0.013)	(0.011)	(0.013)	(0.012)	(0.012)	(0.454)	(0.467)
Mean years of schooling (2019)			1.059**					
			(0.421)					
Access to electricity (% of population) (2019)				0.111*				
				(0.058)				
Individuals using the Internet (% of population) (2019)					0.160***			
					(0.060)			
Mobile cellular subscriptions (per 100 people) (2019)						0.089***		
						(0.034)		
Enablers data economy (2020)							-0.155	
							(0.506)	
Safeguards data economy (2020)								0.165
								(0.468)
Constant	7.714	-9.449	-21.186*	-19.998*	-22.977**	-25.586**	-23.862	-25.178
	(5.385)	(9.365)	(11.197)	(11.777)	(11.325)	(12.397)	(15.511)	(16.854)
Observations	83	83	83	83	83	83	44	44
Adjusted R-squared	0.922	0.924	0.929	0.927	0.93	0.931	0.889	0.889

Notes: Parameter estimates are unweighted ordinary least squares treating each country or economy as the unit of observation. Standard error of the estimates, in parentheses, are robust to heteroskedasticity of general form. *, **, *** denote statistical significance at the standard confidence levels of 10%, 5%, and 1%.

Table 5. Drivers of Digital Payment Usage during COVID-19

DEPENDENT VARIABLE: Share adults making or receiving payments, 2021 EXPLANATORY VARIABLES:	(1)	(2)	(3)	(4)	(5)	(6)
Overall Restrictions on Banking Activities (2016)	0.182	0.138	0.269	0.449	-0.359	-0.251
	(0.429)	(0.439)	(0.448)	(0.468)	(0.870)	(0.900)
Made or received a digital payment (% age 15+) (change 2017-2014)	18.592*	16.923	22.583**	14.852	28.716	30.513
	(10.704)	(10.597)	(11.167)	(9.805)	(18.700)	(18.449)
Made or received a digital payment (% age 15+) (2017)	0.882***	0.934***	0.868***	0.947***	0.992***	0.962***
	(0.043)	(0.038)	(0.045)	(0.038)	(0.071)	(0.077)
Banks' assets (% GDP) (2019)	0.018	0.010	0.007	-0.013	0.041	0.047
	(0.019)	(0.023)	(0.022)	(0.021)	(0.034)	(0.034)
GDP per capita growth (mean over 2015-2019)	0.271	0.213	0.304	0.236	-0.873	-1.141
	(0.455)	(0.485)	(0.438)	(0.440)	(0.841)	(0.772)
log(population) (2019)	1.444***	1.281**	1.568***	1.625***	2.461**	2.316**
	(0.538)	(0.533)	(0.526)	(0.525)	(0.963)	(0.970)
Inflation, consumer prices (annual %) (2019)	-0.022*	-0.009	-0.001	-0.021*	-0.400	-0.413
	(0.012)	(0.014)	(0.013)	(0.011)	(0.434)	(0.452)
Mean years of schooling (2019)#COVID growth differential (2020)	0.064*					
	(0.035)					
Mean years of schooling (2019)	0.386					
	(0.614)					
Access to electricity (% of population) (2019)#COVID growth differential (2020)		0.008*				
		(0.004)				
Access to electricity (% of population) (2019)		0.021				
		(0.088)				
Individuals using the Internet (% of population) (2019)#COVID growth differential (2020)			0.011**			
			(0.005)			
Individuals using the Internet (% of population) (2019)			0.069			
			(0.082)			
Mobile cellular subscriptions (per 100 people) (2019)#COVID growth differential (2020)				0.009***		
				(0.003)		
Mobile cellular subscriptions (per 100 people) (2019)				0.036		
				(0.031)		
enablers_score#COVID growth differential (2020)					0.090*	
					(0.045)	
Enablers data economy (2020)					-0.845	
					(0.701)	
score_safeguards#COVID growth differential (2020)						0.069**
						(0.032)
Safeguards data economy (2020)						-0.278
						(0.521)

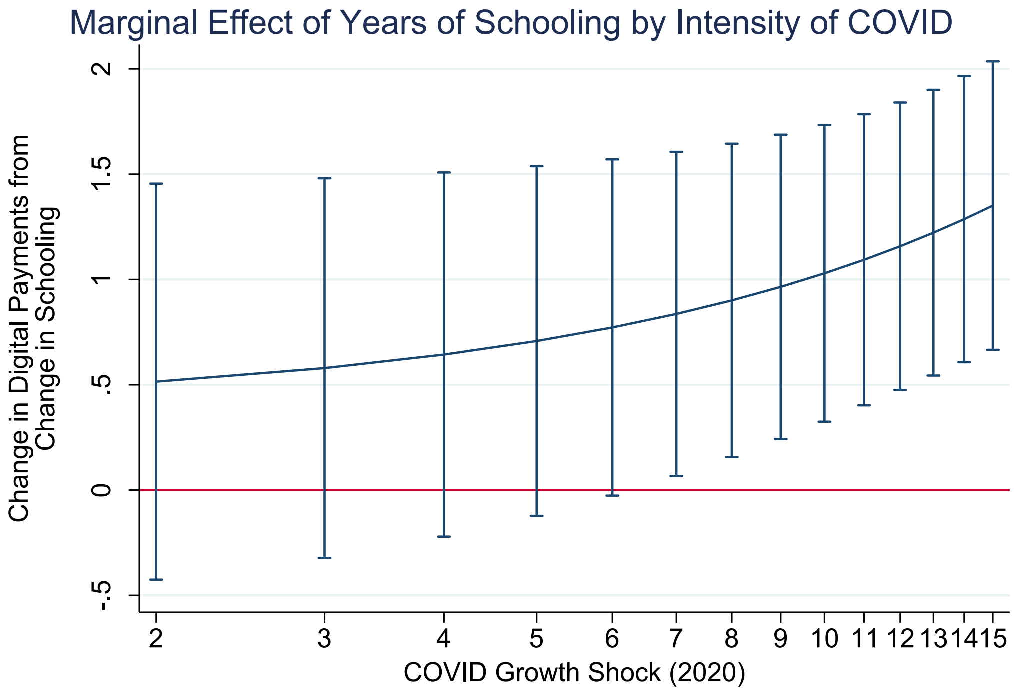
DEPENDENT VARIABLE: Share adults making or receiving payments, 2021 EXPLANATORY VARIABLES:	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-23.094**	-20.921*	-25.679**	-32.948**	-31.438*	-32.176*
	(11.197)	(11.888)	(11.282)	(12.586)	(15.834)	(17.270)
Observations	83	83	83	83	44	44
Adjusted R-squared	0.93	0.929	0.932	0.938	0.894	0.893

Notes: Parameter estimates are unweighted ordinary least squares treating each country or economy as the unit of observation. Standard error of the estimates, in parentheses, are robust to heteroskedasticity of general form. *, **, *** denote statistical significance at the standard confidence levels of 10%, 5%, and 1%.

Table 6. Normalized Magnitudes of the Effects of Education, Infrastructure and Data Governance on the Share of Adults Using Digital Payments during the Past Year (2021): Results from the Static and Dynamic Specifications with and without Interactions with the COVID-19 Shock

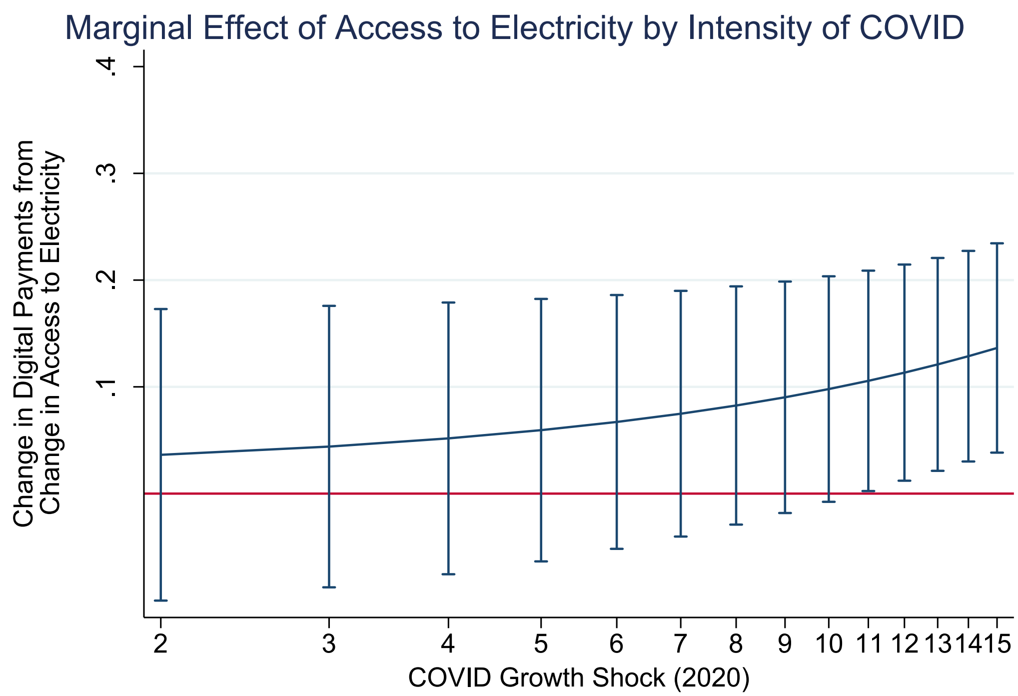
Explanatory Variables	(1)	(2)	(3)
(Standard deviations in parentheses from Table 2)	Static model without interactions (Table 3, columns 3-8)	Dynamic model without Interactions (Table 4, columns 3-8)	Dynamic model with Interactions Computed at the Average Sample Covid Shock (Table 5, columns 1-6)
			Memo: Average Covid Shock=7.62 in Table 2
Schooling (2.95)	15.98	3.12	2.58
Electricity (18.34)	4.45	2.03	1.46
Internet Use (24.53)	18.83	3.94	3.67
Mobile Subscriptions (30.26)	-0.81	2.69	3.16
Enablers Data (2.96)	6.58	-0.46	-0.48
Safeguards Data (3.59)	8.80	0.59	0.90
Range of Adjusted R-squares	0.38-0.62	0.89-0.93	0.89-0.94

Figure 1



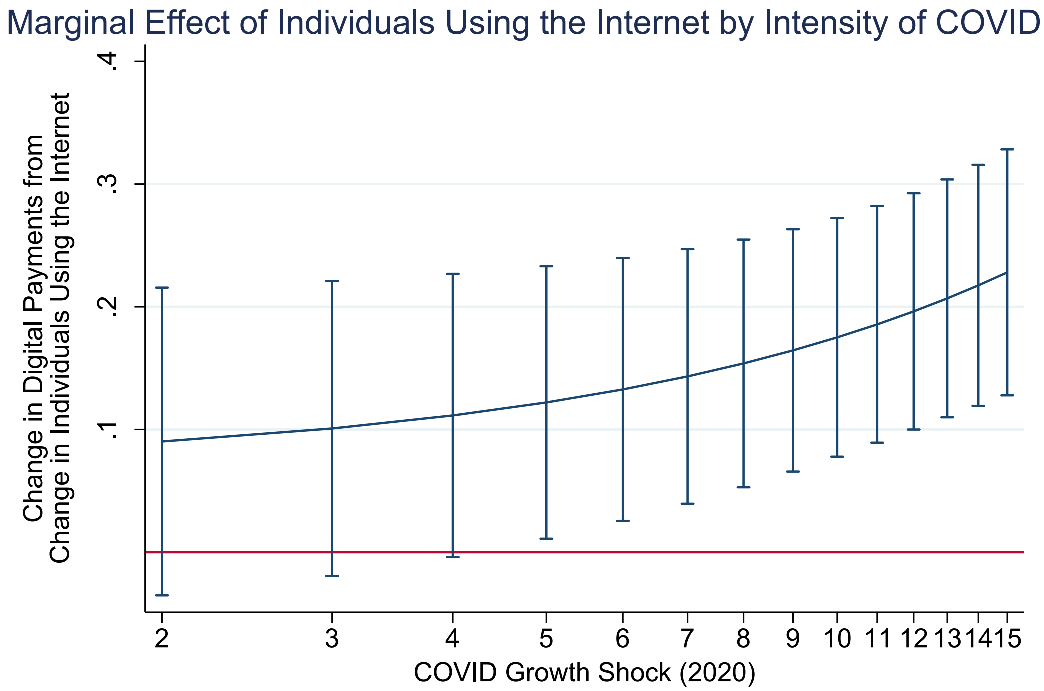
Notes. Figure derived from Table 5, model 1. Horizontal scale is logarithmic.
The line reflects average marginal effects, the whisker endpoints mark the 90% confidence intervals.

Figure 2



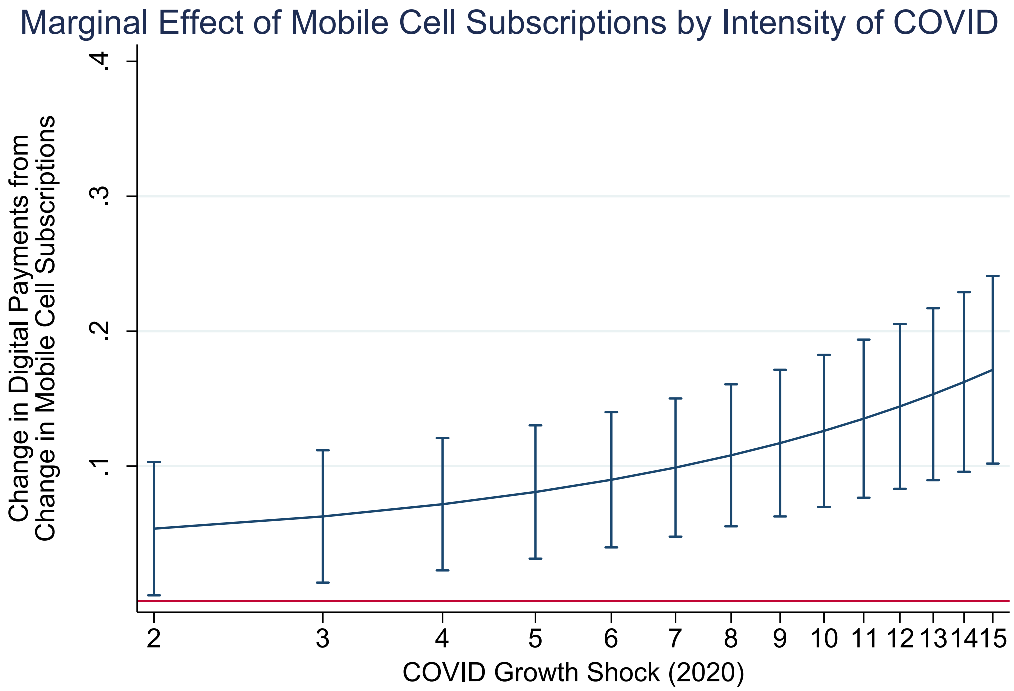
Notes. Figure derived from Table 5, model 2. Horizontal scale is logarithmic.
The line reflects average marginal effects, the whisker endpoints mark the 90% confidence intervals.

Figure 3



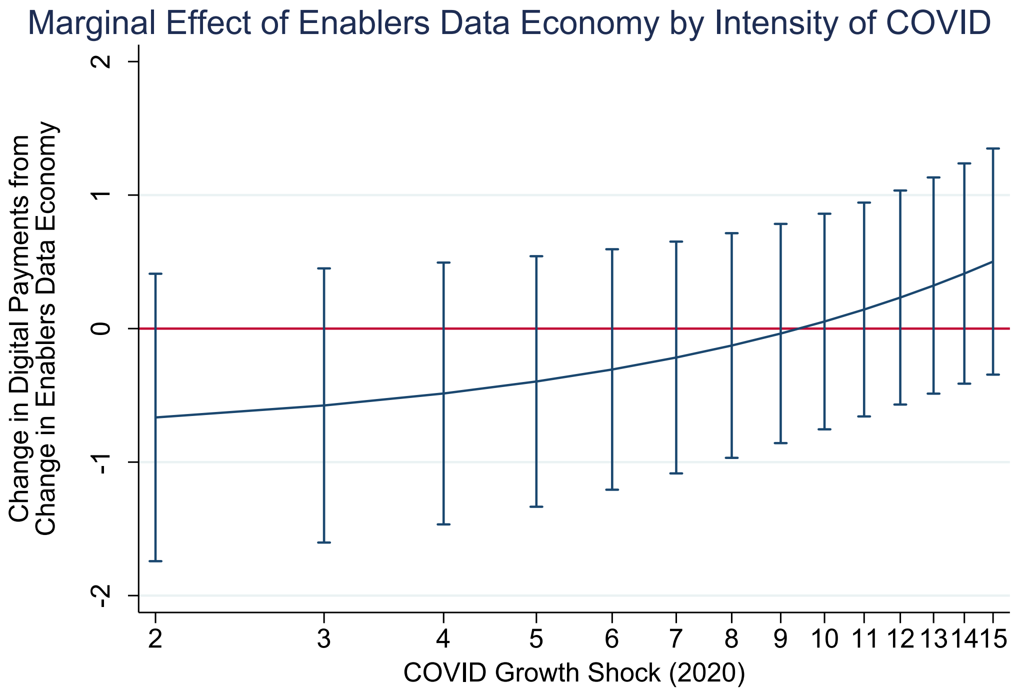
Notes. Figure derived from Table 5, model 3. Horizontal scale is logarithmic.
The line reflects average marginal effects, the whisker endpoints mark the 90% confidence intervals.

Figure 4



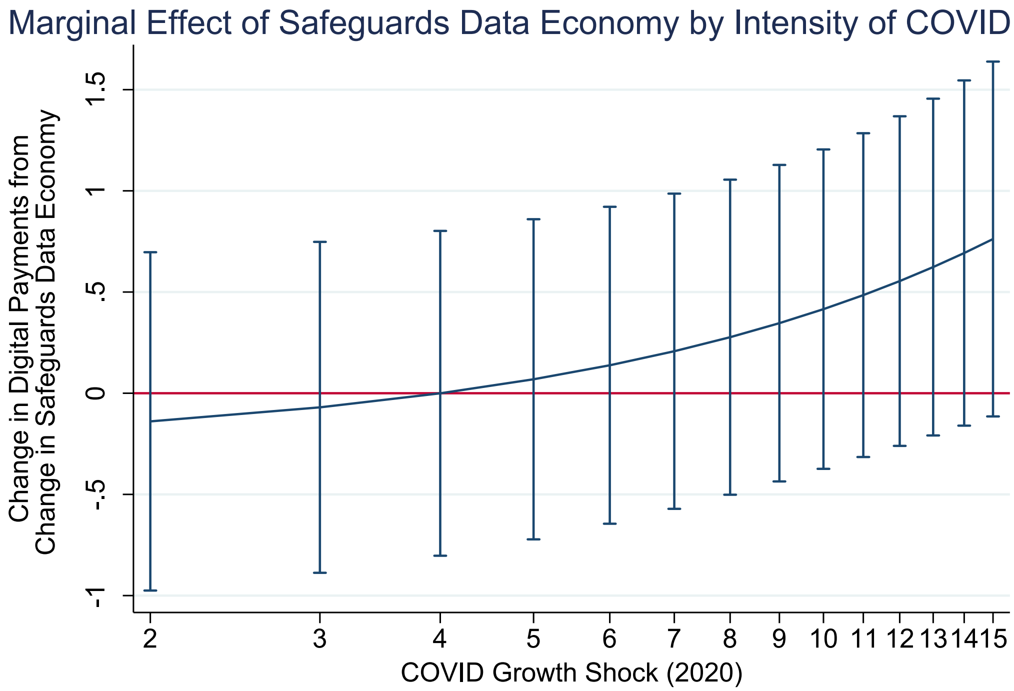
Notes. Figure derived from Table 5, model 4. Horizontal scale is logarithmic.
The line reflects average marginal effects, the whisker endpoints mark the 90% confidence intervals.

Figure 5



Notes. Figure derived from Table 5, model 5. Horizontal scale is logarithmic.
The line reflects average marginal effects, the whisker endpoints mark the 90% confidence intervals.

Figure 6



Notes. Figure derived from Table 5, model 6. Horizontal scale is logarithmic.
The line reflects average marginal effects, the whisker endpoints mark the 90% confidence intervals.