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The Global Impact of COVID-19  
on Fintech Adoption



**Jonathan Fu**

University of Zurich and Center for Sustainable Finance  
and Private Wealth

**Mrinal Mishra**

University of Zurich and Swiss Finance Institute

# The Global Impact of COVID-19 on Fintech Adoption\*

Jonathan Fu<sup>†</sup>    Mrinal Mishra<sup>‡</sup>

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## Abstract

We draw on mobile application data from 74 countries to document the effects of the COVID-19 pandemic on the adoption of digital finance and fintech. We estimate that the spread of COVID-19 and related government lockdowns have led to between a 24 and 32 percent increase in the relative rate of daily downloads of finance mobile applications in the sample countries. In absolute terms, this equates to an average daily increase of roughly 5.2 to 6.3 million application downloads and an aggregate increase of about 316 million app downloads since the pandemic's outbreak, taking into account prior trends. Most regions across the world exhibit notable increases in absolute, relative, and per capita terms. Preliminary analysis of country-level characteristics suggest that market size and demographics, rather than level of economic development and ex-ante adoption rates, drive differential trends.

**Keywords:** digital finance, fintech, financial inclusion, technological adoption, COVID-19, cross-country

**JEL Codes:** G23, G20, O33

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<sup>†</sup>Postdoctoral researcher, Department of Banking & Finance, University of Zurich and The Center for Sustainable Finance and Private Wealth.

<sup>‡</sup>Ph.D. candidate, Department of Banking & Finance, University of Zurich and The Swiss Finance Institute.

# 1 Introduction

Shocks of various kinds can drive technological adoption in unanticipated ways. Moreover, these shocks can also result in longer term changes to societies and economies. The COVID-19 pandemic started out as a shock to public health and healthcare systems. However, the nature of the pandemic coupled with the speed of transmission have required societies to adopt “social-distancing” or more stringent lockdown measures imposed by the government. This has been the case both in areas affected and unaffected by the actual spread of COVID-19. Despite the high human and economic costs following its spread,<sup>1</sup> COVID-19 has resulted in some beneficiaries and possible silver linings. There is increasing anecdotal evidence that the technology sector and, in particular, companies enabling communication and exchange of goods and services over distance have seen notable increases in adoption and usage.<sup>2</sup> Such services have proven essential in helping many households and other firms to mitigate some of the health risks and adverse socioeconomic effects of the pandemic and allowing some critical aspects of day-to-day life to continue as normal.

In this paper, we provide evidence on the acceleration of digital transformation in the financial sector by documenting the early impact of COVID-19’s spread on fintech adoption worldwide. To do so, we draw on historical and real-time data on mobile application downloads, which provides us with a high dimensional measure that allows us to detect changes on the extensive margin within a small time frame. The use of such mobile application-based services intuitively provides an attractive option for accessing financial services particularly during a pandemic—given self- or government-imposed restrictions to movement and social distancing measures, and risk of contamination via physically handling cash (Arner et al. (2020)). Moreover, the nature of the fintech market generally gives providers greater flexibility to quickly deploy new products and services or adapt or scale existing ones, in response to shocks (Fuster et al. (2019)). We extract daily information on all finance mobile app downloads from January 1st, 2019 to present<sup>3</sup> for 74 countries available and covering both the Android and iOS markets.<sup>4</sup> The countries in our sample cover all global regions and account for approximately 80 percent of the global population and over 90 percent of the world economy in terms of nominal GDP.

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<sup>1</sup>The global death toll as of April 20th is at over 165K. Due to the curbs on gathering in public places and travel, a gamut of sectors such as transportation, hospitality, and leisure have been particularly hard hit. <https://www.brookings.edu/blog/the-avenue/2020/03/17/the-places-a-covid-19-recession-will-likely-hit-hardest/>

<sup>2</sup>See for example: <https://www.economist.com/briefing/2020/04/11/the-changes-covid-19-is-forcing-on-to-business>.

<sup>3</sup>Unless otherwise noted, the analysis in this paper uses data up until April 20th, 2020.

<sup>4</sup>While not comprehensive of all fintech activity, we believe this provides a reasonable proxy for capturing its spread, since an increasing share of fintech providers (both newer startups and traditional incumbents) establish a customer-provider relationship and deliver their services via mobile applications. This is particularly the case given the increasing pervasiveness of smartphones and mobile internet coverage, including in lower- and middle-income economies. At the end of 2019, 90 percent of the world’s population was covered by mobile networks, 67 percent of the global population (5.2 billion people) had a subscription to mobile services, and 49 percent of the global population (3.8 billion people) were mobile internet users (GSMA (2020)).

Using these data, we apply panel data regression models controlling for seasonality at the aggregate- or country-level to estimate the change in fintech app adoption pre- and post-COVID-19. We estimate that the spread of COVID-19 and related government lockdowns have led to between a 24 and 32 percent increase in the relative rate of daily downloads. In absolute terms, and accounting for the average number of days since confirmed cases or lockdowns in our sample, this equates to an aggregate increase of about 316 million app downloads since the pandemic's outbreak. We then test for signs of differential trends across regions. While certain regions do exhibit larger increases than others, we find that all global regions exhibit significantly higher demand compared to pre-COVID-19 trends. The one notable exception is Europe, where there has been a flat or slight decrease in demand. Finally, we further conduct some exploratory analyses on country-level characteristics that may drive differential trends. Our results generally do not suggest that countries' economic development level or ex-ante rates of adoption are particularly predictive of post-COVID 19 adoption. Rather, and in line with some existing literature, it suggests factors related to market size (Foster & Rosenzweig (2010)) and demographics (Carlin et al. (2017)), which may point to the importance of network effects.

Our paper relates primarily to literature on fintech adoption and the role of shocks in driving acceleration. Existing studies have highlighted that idiosyncratic shocks *within countries*—affecting either the demand or supply-side—can have immediate and longer-term effects on local rates of fintech adoption (Higgins (2019), Crouzet et al. (2019), Chava et al. (2018)).<sup>5</sup> These studies tend to emphasize how network effects may either amplify or lessen rates of adoption during a shock. For example, as more individuals and businesses use digital payments and other digital products, the benefits to all users increase, creating externalities that can further accelerate adoption. A main implication noted by Crouzet et al. (2019) is that whether a shock leads to a persistently higher or only transitory increase in adoption is thus dependent on both the magnitude of the shock and the ex-ante state of adoption.

To date, however, there are no studies to our knowledge that look at how global-level shocks occurring *across countries* may similarly play out and either lead to convergence in their fintech adoption rates or exacerbate existing differences. This is a particular concern due to an existing “digital gap” that exists between many lower and middle-income economies and advanced economies (GSMA (2020)). Given the broad range of potential benefits (and risks)

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<sup>5</sup>“Fintech” can be broadly defined as technologically-enabled financial innovation that results in new business models, applications, processes, products, or services with an associated material effect on financial markets and institutions and the provision of financial services (Schindler (2017)). Typically, it refers to innovators and disruptors in the financial sector that make use of the availability of information communication technology—particularly, Internet-related technologies (e.g., cloud computing, mobile Internet)—and data processing technologies (e.g., predictive analytics, automation, and machine learning). As noted by Gomber et al. (2017), this may come either from “disruptive fintech”—new start-ups and larger technology companies (“BigTech”) offering new products and services that challenge incumbent traditional providers, or from “sustaining fintech”—established financial services providers that try to protect their market position by similarly adopting and innovating in use of information technologies.

from more widespread adoption of digital finance and fintech—particularly for mitigating effects from major shocks such as COVID-19—this may have important implications both in the short- and long-term. For example, consumers and retail firms generally benefit from fintech adoption by gaining access to more affordable, responsive, and tailored banking services (Das (2019)); particularly those who have been traditionally unbanked or underbanked (Demirguc-Kunt et al. (2018), GPMI (2016)).<sup>6</sup> Financial service providers typically reduce operational costs significantly and can use novel processes to better assess credit risk ex-ante and reduce delinquency ex-post.<sup>7</sup> Governments, monetary authorities, and financial regulators are also expected to benefit from increased efficiency of tax collection and subsidy payment, combating inflation via reduced circulation of excess or bad money, and gaining more diverse tools for reviving credit markets (Manyika et al. (2016), BIS (2018)). Finally, at the macroeconomic-level, large-scale aggregate increases in financial access may generate productivity gains across the economy and help spur economic growth (Manyika et al. (2016)), or in the case of COVID-19, mitigate the expected freefall.

More generally, comparable cross-country data on many aspects of fintech adoption are still relatively limited and, hence, comparative research on drivers of adoption across countries is still scarce. Among the few comparative studies in this area, Claessens et al. (2018) use a static estimate of the volume of fintech credit per capita in the economy for 63 countries and run cross-sectional regressions to find that the size of an economy’s fintech credit market is positively related to its income level, and negatively related to the competitiveness of its banking system and the stringency of its banking regulation. Frost (2020), meanwhile, similarly draws on cross-sectional evidence from a household survey of 38 countries by EY (2019) to note the important role of country demographics on predicting broader “digital finance” adoption—defined as active use of multiple categories of fintech products and services. Both sets of authors (Claessens et al. (2018) and Frost (2020)) note that measuring fintech activity and, in particular, having a sense of real-time trends, can be difficult given the diversity and constantly evolving landscape of fintech providers, the small size of many of the platforms, and because many of the providers still lie outside of prudential regulatory reporting requirements. Cross-country demand-side surveys such as the Global Findex (Demirguc-Kunt et al. (2018)) may offer important insights to fill this gap, but are relatively infrequent given their high cost. Thus, particularly for measuring outcomes from a crisis on fintech activity, there is an important need for obtaining high-frequency data

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<sup>6</sup>A large body of impact evaluations have provided consistent evidence that digital payments, remittances, and insurance are particularly useful at mitigating effects from exogenous shocks by expanding households networks for safety-nets and risk-pooling (Jack et al. (2013), Jack & Suri (2014), and Bharadwaj et al. (2019)). (Albeit, the implications of such studies are less clear in the case of a shock such as COVID-19, which has affected most of the world, both across- and within-countries.)

<sup>7</sup>For example, many fintech providers use digital trails to better assess risk, collect digital repayments on an automated basis, and reduce loan delinquency via SMS or mobile app “nudges” to prompt borrowers when they have missed a payment. This has allowed them to underwrite loans and insurance policies for clients deemed too risky for traditional providers.

that is comprehensive of all types of providers.

Building on the extant literature, we focus our analysis on testing the following preliminary hypotheses:

- $H_1$ : *The COVID-19 pandemic has increased adoption of finance mobile applications on the extensive margin.*
- $H_2$ : *The effect on adoption is smaller in countries with higher levels of economic development and with higher rates of ex-ante adoption and larger in countries with larger market size (population and demographics).*
- $H_3$ : *The effect on adoption is primarily driven by government restrictions rather than the spread of COVID-19 itself.*

The remainder of the paper proceeds as follows. Section 2 describes the study's data sources. Section 3 presents the paper's main analyses and results. Section 4 discusses broader implications and concludes.

## 2 Data

### 2.1 Data Sources

To obtain a reasonable estimate of fintech adoption driven by COVID-19, we need a high-frequency measure that allows us to detect changes within a small time frame. To do so, we draw on mobile app download data from the AppTweak platform.<sup>8</sup> The platform contains historical and real-time data on mobile app downloads at the aggregate- or country-level for all app categories in the Android and iOS markets. We extract daily information on all finance category mobile apps downloads from January 1st, 2019 to present for the 74 countries available through the platform.<sup>9</sup> (See Appendix Table A.1 for a full country list and additional details.) These data are pulled at the country-level, which allows us to aggregate up to broader regions, as required for a given analysis. Note that preliminary data investigation revealed some day-to-day volatility in downloads—particularly, for some of the smaller countries or apps. Thus, we calculate a leading and equally-weighted 14-day moving average for the number of downloads to smooth

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<sup>8</sup><https://www.apptweak.com/>

<sup>9</sup>The categorization of finance apps are currently taken directly from the platform as listed by the mobile applications' developers. The advantages of drawing on the self-categorization is that it provides a way to capture real-time and comprehensive data on all providers in the market, of any size. The disadvantage is that it is cumbersome to control whether all applications in the entire platform are necessarily correctly categorized, given its comprehensive scale. However, as the platform allows us to also target individual financial service providers of interest and their particular apps, we plan to use this more granular level data in our next iteration to better understand what specific provider and product types are driving results.

these day-to-day fluctuations. This is used for our descriptive figures and serves as the main dependent variable for our empirical analysis.<sup>10</sup>

Our main explanatory variables are proxies for the spread of COVID-19 and related government policy. For the former, we draw on data from the Oxford COVID-19 Government Response Tracker (OxCGRT).<sup>11</sup> OxCGRT provides daily updates on the number of confirmed cases and confirmed deaths, as well as various different types of policies being implemented at the country-daily level (e.g., school closures, workplace closures, travel restrictions, etc.). These policies are used by OxCGRT to construct a policy “stringency index”. For the latter, we draw on data from Kaggle, which provides the date of each country’s lockdowns implemented due COVID-19, if applicable.<sup>12</sup> Finally, we also merge data from the World Bank’s World Development Indicator database and the 2017 Global Findex database for some of our exploratory analyses on predictors of differential post-COVID-19 trends in adoption.

## 2.2 Descriptive Statistics and Trends

Figure 1 presents the average daily downloads for fintech apps across our full country sample. We note a clear uptrend in downloads starting from around mid-February. To see which mobile operating system dominates the results, we split the total downloads to Android and iOS apps and observe that the uptick seems to be mainly driven by the Android market with a muted or almost no effect for the iOS market. The figure shows a heightened adoption of fintech apps and a greater push towards digitalization during the pandemic. This affirms the general notion that exogenous shocks to the economy or society end up accelerating trends which would have otherwise played out in a more protracted fashion.

Figure 2 depicts a scatter plot of daily downloads and COVID-19 cases across countries. We remove the time dimension from our data by aggregating all the data from 2020. Subsequently, we also plot the best fit line and observe a general upward trend. The figure gives us a high-level understanding of how the spread of COVID-19 is associated with fintech adoption. Initial evidence, as depicted by Figure 2 suggests there is a strong positive correlation between both. A crude analysis suggests that countries above the best fit line show increased fintech adoption whereas those below the line show lower adoption owing to the effects of the pandemic. A myriad of reasons like the intensity of enforced lockdowns, extent of previous adoption of fintech, or access to mobile internet and smartphones could be instrumental in driving these effects. However, as Figure 6 in the Appendix shows, the correlation between lockdown intensity and

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<sup>10</sup>We conduct sensitivity tests on our main results using the original raw download numbers or applying 10-, 20-, and 30-day moving averages in lieu of the 14-day window. Results are provided in Appendix Tables A.2 and A.3 and help demonstrate that the main results and takeaways are largely unchanged.

<sup>11</sup><https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker>

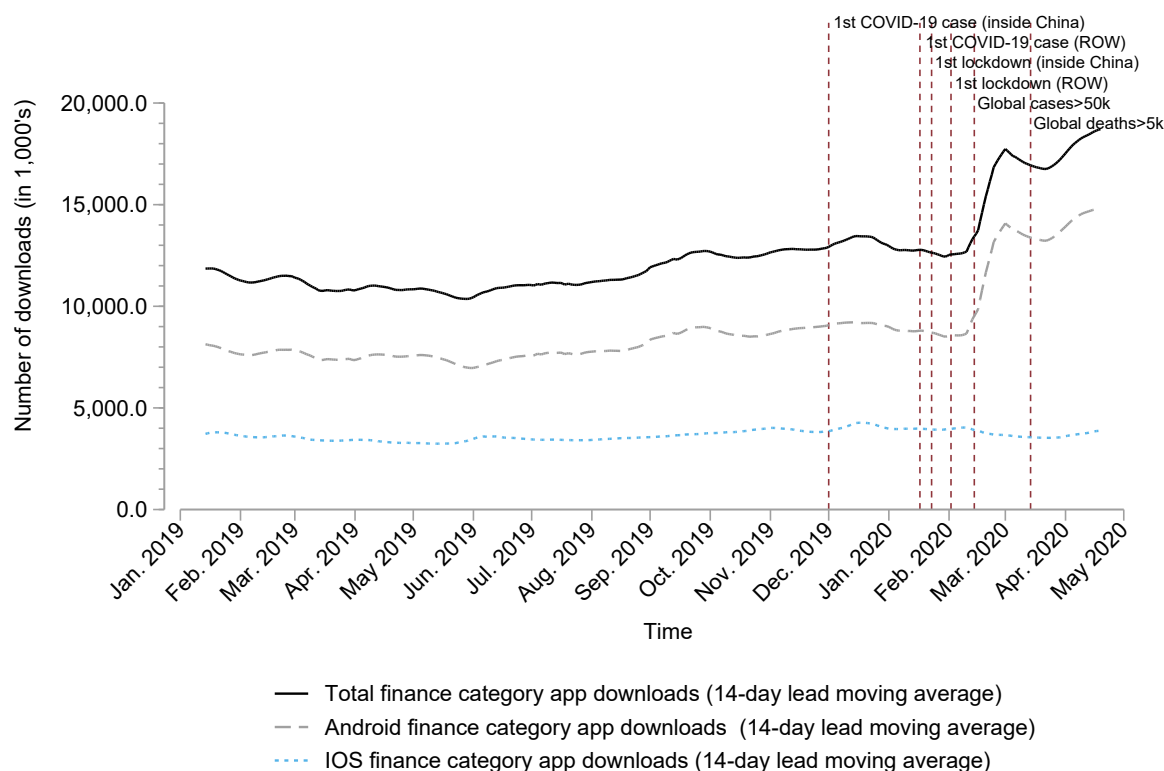
<sup>12</sup><https://www.kaggle.com/jcyzag/covid19-lockdown-dates-by-country>.

app downloads is relatively weaker than the relationship in Figure 2, which may suggest that adoption is not primarily driven by the exogenously-imposed lockdowns instituted in countries.

Further descriptive statistics at the aggregate- and country-level are provided in Tables 1 and 2, respectively.

**Figure 1: The Impact of COVID-19 on the Adoption of Fintech Mobile Apps**

This figure depicts the daily number of downloads for finance category mobile applications across the iOS and Android platforms from 74 countries. The sample data covers the period from January 1st, 2019 to April 20th, 2020.



**3 Results**

**3.1 What is the Estimated Impact of the Spread of COVID-19 on Fintech Adoption?**

To provide a concise way of estimating the effect of COVID-19 on the magnitude of fintech adoption during our study period, we use an empirical specification of the following form:

$$y_{it} = \beta_0 + \beta_1 COVID19_{it} + \theta_i + \gamma_m + u_{it} \tag{1}$$

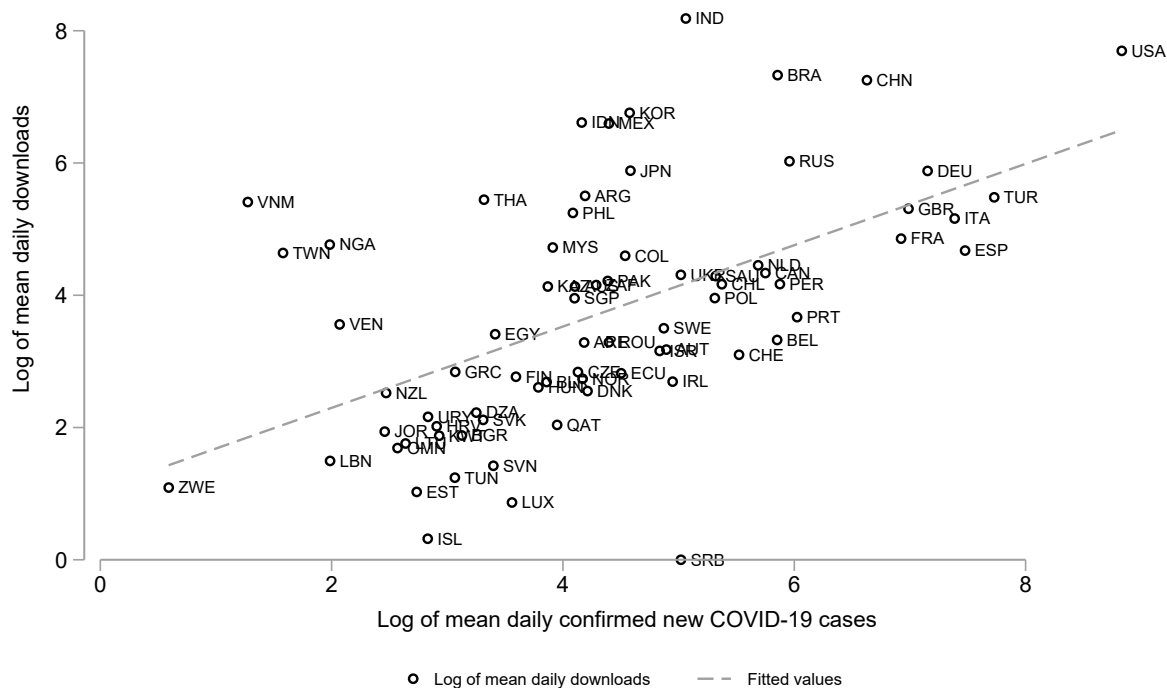
where the dependent variable  $y$  is either 1) the absolute number of daily downloads or 2) the relative (logarithmic) growth in daily downloads for location  $i$  and at time (day)  $t$ .<sup>13</sup> Note that

<sup>13</sup>We also calculate and run comparable results using daily downloads per capita. The results are provided in



**Figure 2: Scatterplot of Finance Category Mobile App Downloads vs. Confirmed COVID-19 Cases**

This figure depicts the relationship between countries' average daily number of downloads for finance category mobile applications and average daily confirmed new cases of COVID-19. We roughly restrict to the general period after the first signs of the COVID-19 outbreak (i.e., since January 1st, 2020). The underlying data includes mobile apps from both the iOS and Android platforms for 74 countries. Country codes are listed in Appendix Table A.1.



location  $i$  can refer to either an individual country or a region, as required for a given analysis.  $COVID19$  denotes a dummy that is set to one after time  $t$ , either when location  $i$  had its first confirmed cases (*Post-Confirmed case*) or entered into lockdown (*Post-Lockdown*), respectively. We include location-level dummies ( $\theta_i$ ) to control for country or region fixed effects, and month of the year dummies (denoted by  $\gamma_m$ ) to adjust for aggregate seasonal trends in the finance app market. We alternatively interact the location and month dummies in our preferred specification to control for more disaggregated seasonality in downloads (e.g., country- or region-level time trends, which would substitute  $(\theta_i \times \gamma_m)$  in lieu of the location and month dummies.<sup>14</sup>

Tables 3 and 4 present results for the country-level model estimating the impact of COVID-19 on fintech adoption using the *Post-Confirmed case* or *Post-Lockdown* variables, respectively.<sup>15</sup>

Appendix Tables A.4 and A.5.

<sup>14</sup>For example, preliminary data exploration reveals that the United States experiences a significant uptick annually in finance-related app downloads every February and March prior to its tax-filing deadlines in April. As this happens to coincide with the timing of the spread of COVID-19 cases and lockdown in the United States, applying the country-month interactions helps mitigate confounding these seasonality trends and overestimating the change from COVID-19.

<sup>15</sup>In Appendix Tables A.2 and A.3, we present results from alternate constructions of the main explanatory variables by altering the definition of app downloads. For our baseline, we use a 14-day moving average of app

The results across both the tables are generally quite consistent and show that the COVID-19 outbreak led to an absolute and relative increase in fintech adoption, even after controlling for country fixed characteristics and aggregate- or country-level seasonality in app downloads. The coefficients depicted in Tables 3 and 4 are in terms of average per country. In absolute terms, we estimate that, on average, a given country saw a daily increase of about 88,000 and 76,000 finance mobile app downloads following the date of its first confirmed case and lockdown, respectively, taking into account prior trends. (These figures are based on our preferred specifications in columns 4, which control for country-level seasonality.)

If we aggregate the effects across the 74 countries in our full sample, of which 72 have had a confirmed COVID-19 case and 68 have entered lockdown (see Table 1 or Appendix Table A.1), the economic size can be interpreted as an increase of approximately 5.2 to 6.3 million finance app downloads per day “globally” driven by COVID-19. Furthermore, accounting for the average number of days since confirmed COVID-19 cases or lockdowns in our sample (see Table 2), this equates to a aggregate increase of 316 and 135 million finance app downloads, respectively. In relative terms, this is an increase of around 32 percent since countries’ first confirmed COVID-19 case and around 24 percent since the start of COVID-19 related lockdowns, compared to prior trends. (Figures based on Tables 3 and 4, columns 8.)

### 3.2 Are All Regions Equally Affected?

The spread of COVID-19 has not been uniform across all continents and regions. Countries in Asia, Europe, and North America have generally been hit earlier and—thus far—harder than in Africa, South America, the Middle East, and Oceania. As a result, the adoption in fintech might also show some heterogeneity depending on the duration or intensity of the pandemic in certain regions. This analysis become important as some areas like Europe and USA-Canada are free movement zones for capital and labour. As a preliminary investigation into region-level effects, we re-construct our main variables at the region level and then re-run Equation (1). We interact the *COVID19* dummy with the respective region dummies to test for the differential effects of COVID-19 on fintech adoption rates.

Table 5 depicts results from this region-level analysis. Europe serves as the base category in the results. We can observe that the countries in our sample from North America and Asia exhibit the largest increase both in absolute and relative terms and are responsible for most of the adoption on the extensive margin. That having been said, the countries in our sample from Africa, Middle East, Oceania, and South America also see fairly large increases in either

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downloads. However, to ensure that our results are not overly sensitive to the choice of the number of days in the moving average calculation, we alter this number to 10, 20 and 30 days and observe that our main results still hold.

absolute or relative terms. In our preferred specifications that control for regional seasonality (in columns 6 and 8), their estimated relative increases fall in the range between 15 and 39 percent, post-confirmed cases, and between 33 and 44 percent, post-lockdown. The European countries in our sample are the notable exception, where we observe that, after an initial minor uptick after cases began to spread, there was a flat or slight decrease in rates of downloads following the spread of government-instituted lockdowns.

Diving a level deeper into our underlying data, we observe that the post-COVID-19 increases appear particularly driven by the United States, India, and Mexico in absolute terms, but that a range of other countries, such as Indonesia, Turkey, Russia, the Netherlands, and Brazil in very recent weeks also experience large relative increases. Apart from the major economies and those with larger populations, a similar aggregate trend exists for the remaining countries in our sample. Meanwhile, we can also observe that Germany and Italy experienced large decreases and play a key role in driving the negative result for Europe. See Appendix Figures 3 and 4 for further details on per capita trends for the countries that are the largest markets and most affected by the spread of COVID-19 cases, respectively.<sup>16</sup>

### 3.3 What Country-level Characteristics Predict Differential Adoption due to COVID-19?

We subsequently test whether a number of other country-level characteristics drawn from the extant literature are significant predictors of differential trends in digital finance adoption due to COVID-19. Specifically, we merge country-level characteristics on country development level (log of GDP per capita in \$PPP), market size (log of country population), demographics (percentage of population over 65), access to ICT (percentage of the population with a mobile phone subscription), and ex-ante adoption of digital banking (as a proxy, we use the percentage of a country's population that reported regularly receiving wages using their mobile phones). We re-run Equation (1) including these country-level factors as interaction terms to test whether any pre-existing trends are driving our end outcomes, i.e., fintech adoption.

Tables 6 and 7 depict the results from these model specifications for the absolute number of downloads and relative downloads respectively. In line with existing literature, we find that

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<sup>16</sup>We also took a preliminary look at trends for some of the underlying top finance mobile applications in our country sample. Payment and money transfers apps—both from global “BigTech” companies and local providers—appear to have seen the most consistent increases in absolute terms following COVID-19's spread. However, most other product categories are represented as well. For example, across all regions, we also see increased uptake of general banking apps for both traditional incumbents and some neo-banks. Moreover, we observe that some of the top apps in the sample countries from Africa, Asia, and Oceania are personal loan or consumer credit apps, which have seen particularly high growth in very recent weeks. There are also more select examples of wealth management, investment/trading, and cryptocurrency apps seeing large increases in adoption. In our next iteration, we plan to set up empirical specifications to formally test hypotheses related to provider types and product categories and to provide more concrete estimates of any differential trends.

country economic development level is not necessarily a strong predictor of differential adoption rates of mobile finance apps due to COVID-19. There are some signs that countries with higher incomes and industrialization level (as proxied by GDP per capita) had lower rates of adoption, post-pandemic, but these results are insignificant. Moreover, we do not find particularly strong evidence that ICT access or ex-ante digital finance adoption is strongly associated with differential rates of adoption due to COVID-19. This may suggest that, from a country-level perspective and for the time being, COVID-19 does not appear to have exacerbated differences in digital finance adoption between those with higher or lower ex-ante adoption.

What we do note is that larger market size (proxied by country population) is a strong predictor of fintech adoption during the pandemic. Moreover, it is intuitively associated with increased adoption in both absolute and relative terms with the economic magnitude of this relationship being quite large. This may be related to positive adoption externalities and spillover effects for many network-based financial technologies, as noted by (Crouzet et al., 2019; Higgins, 2019). In line with prior studies, we also find evidence that demographics plays a key role in the dissemination of fintech as aging populations are seen to be negatively associated with decreased adoption.

### **3.4 Does the Spread of COVID-19 or Government Policy Drive Adoption?**

Our initial results are consistent in showing that a positive and significant relationship exists between the spread of COVID-19 and associated fintech app downloads. However, the shock due to COVID-19 is indeed unique with many different effects overlapping each other. Our results and empirical setting do not allow us to readily distinguish what primarily drives this uptick in fintech adoption. The effects we observe may be due to the direct spread of COVID-19 (first-order effects), the lockdowns instituted by various governments (second-order effects), or more protracted economic shocks from job losses, business closures, etc. arising from the lockdowns over time (third-order effects).

Table 8 depicts preliminary results for country-level specifications where we try to disentangle the first- and second-order effects, i.e., the spread of the pandemic and the government lockdowns. There is considerable overlap between the outcomes due to COVID-19 and government lockdowns and hence, any evidence presented, is suggestive at best. Our results depict that the adoption in fintech, in absolute and relative terms, seems to be driven mainly by the spread of the pandemic even when we control for the stringency of government policies to mitigate COVID-19 (columns 1 and 6). When we flip our dummy to capture post lockdown effects instead, and control for the growth in cases (columns 3 and 8), the results are again synonymous with depicting a strong positive correlation with the actual spread of COVID-19 itself. However, when we use the dummy and variables for confirmed deaths instead of confirmed cases, the lockdown effects dominate the

outcomes (column 7). The evidence, while somewhat mixed, seems more consistent in suggesting that a larger portion of the results are driven by the initial spread of COVID-19 and to a lesser extent the government lockdowns. The spread of the pandemic appears to have driven more individuals to adopt new digital finance and fintech platforms at an earlier stage of the pandemic propelled by the desire to follow *social distancing* norms and practice physical isolation.

## 4 Conclusion

We draw on mobile application data from 74 countries to document the effects of the COVID-19 pandemic on the adoption of digital finance and fintech, as proxied by finance category mobile application downloads on the extensive margin. We find that the spread of COVID-19 and related government lockdowns have led to statistically and economically significant increases in downloads of such mobile application, whether in absolute, relative, or per capita terms. These early effects have been fairly widespread across global regions, with the exception of Europe. Furthermore, at the country-level, we do not see strong initial signs that countries are exhibiting divergent trends based on economic development level or ex-ante rates of adoption.

There are several limitations to our work in its current iteration. First, we have not yet begun to address the considerable diversity of the fintech market, and analyze whether there are differential trends that may exist across different types of providers and products. For example, [BIS \(2018\)](#) identify several stylized scenarios of how competition between incumbent, fintech, and bigtech players may play out as adoption of financial technology increases, with divergent implications risks and opportunities for banks and banking systems. Moreover, it would be logical to better use the granular app-level data to assess whether the new adoption driven by COVID-19 is disproportionately stemming from certain product types—for example, payments and money-transfer, consumer or business lending, or other. Secondly, we currently focus solely on effects on the extensive margin (indication of changes in consumer demand and access) and do not directly touch on intensive margin effects for providers (e.g., transaction volumes, changes to financial performance, etc.) nor further welfare effects on consumers. On the one hand, we believe that focusing on short-term effects on the extensive margin makes sense since it serves as an important leading indicator. On the other hand, as time goes on, it will be increasingly important to also analyze these additional dimensions to see whether the documented large-scale increase in adoption has generally led to more opportunities or risks to consumers, firms, and governments. In a later iteration, we plan to complement the current analysis by drawing on available intensive margin data on mobile application usage and retention, as well as up-to-date data on provider financials to expand our analysis to cover these areas.

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**Table 1: “Global” finance mobile app market and COVID-19 statistics at a glance**

This table provides aggregate-level descriptive statistics on the total and average number of finance category mobile app downloads, COVID-19 cases and deaths, and related government lockdowns or policies across our sample and study period. The app data covers the iOS and Android mobile app markets for 74 countries from January 1st, 2019 to present. (‡ denotes figures as of April 20th, 2020.) The sample countries collectively cover all global regions and account for approximately 80 percent of the global population and over 90 percent of the world economy in terms of nominal GDP. Data sources: AppTweak, OxCGRT, and Kaggle.

Variable	#
Total # of finance category mobile app downloads across sample countries (in 1,000’s)‡	5,999,545
Mean # of <i>daily</i> app downloads (in 1,000’s)	12,578
Total # of COVID-19 cases across sample countries (in 1,000’s)‡	2,147
Total # of COVID-19 deaths across sample countries (in 1,000’s)‡	153
Total # of sample countries with confirmed cases‡	72
Total # of sample countries with lockdowns‡	67
Total population across sample countries (in million’s)	5,970



**Table 2: Country-level descriptive statistics**

This table provides country-level descriptive statistics on the average number of daily finance mobile app downloads, average current number of COVID-19 cases and deaths, and related government lockdowns or policies. We also provide summary statistics on some additional country economic and demographic characteristics. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to present. (‡ denotes figures as of April 20th, 2020.) The countries in our sample collectively cover all global regions and account for approximately 80 percent of the global population and over 90 percent of the world economy in terms of nominal GDP. Data sources: AppTweak, OxCGRT, Kaggle, WDI, Global Findex.

Variable	Obs.	Mean	Std. Dev.	Min	Max
<i>Panel A. Country-level statistics</i>					
# of daily downloads (in 1,000's)	34,272	168.1	418.1	0	4,464.1
# of COVID-19 cases (in 1,000's)‡	74	24.0	75.1	0.0	583.0
# of COVID-19 deaths (in 1,000's)‡	74	1.6	4.6	0.0	23.7
OxCGRT government stringency index (0 to 100)‡	74	64.5	41.3	0.0	100.0
# of days since 1st COVID-19 case‡	74	50.0	20.2	0.0	104.0
# of days since lockdown startdate‡	74	26.1	11.5	0.0	82.0
<i>Panel B. General sample characteristics</i>					
GDP per capita, \$PPP	70	32,482	22,333	2,688	112,600
Population (in millions)	74	83.0	229.0	0.6	1,390.0
% of population aged 65 and up	72	13.1	6.6	1.1	27.6
% of population with mobile phone	71	124.1	30.6	64.5	270.0
% of population using mobile phone to pay utilities	70	13.3	11.4	0.0	43.6

**Table 3: The spread of COVID-19 cases and change in finance mobile app adoption**

This table presents coefficient estimates for a panel regression model estimating the country-level relationship between the spread of COVID-19 on absolute number of daily downloads and relative (logarithmic) number of daily downloads for finance category mobile apps. We use a 14-day leading moving average to calculate downloads to smooth day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given country saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. Depending on the model specification, we include country fixed effects, month dummies to control for aggregate level seasonality in finance app downloads, and country X month interaction dummies to control for country-level seasonality. Standard errors are clustered at the country level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ .

	DV=Absolute # of daily app downloads (in 1,000's)				DV=Relative (ln) of # daily app downloads			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Post-Confirmed case</i>	142.138*	81.173*	81.566*	87.745*	0.712***	0.337***	0.286***	0.316***
	(0.013)	(0.040)	(0.044)	(0.033)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	36,100	36,100	36,100	36,100	36,100	36,100	36,100	36,100
$R^2$	0.013	0.891	0.892	0.923	0.016	0.874	0.892	0.899
<i>Additional controls:</i>								
Country fixed effects	No	Yes	Yes	No	No	Yes	Yes	No
Month dummies (aggregate seasonality)	No	No	Yes	No	No	No	Yes	No
Country X month interactions (local seasonality)	No	No	No	Yes	No	No	No	Yes

**Table 4: The spread of COVID-19 government lockdown and change in finance mobile app adoption**

This table presents coefficient estimates for a panel regression model estimating the country-level relationship between the spread of COVID-19 on absolute number of daily downloads and relative (logarithmic) number of daily downloads for finance category mobile apps. We use a 14-day leading moving average to calculate downloads to smooth day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given country saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. Depending on the model specification, we include country fixed effects, month dummies to control for aggregate level seasonality in finance app downloads, and country X month interaction dummies to control for country-level seasonality. Standard errors are clustered at the country level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, and Kaggle.

	DV=Absolute # of daily app downloads (in 1,000's)				DV=Relative (ln) of # daily app downloads			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Post-Lockdown</i>	103.903*	78.295*	72.197*	75.994*	0.488***	0.328***	0.228***	0.243***
	(0.033)	(0.032)	(0.037)	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	36,100	36,100	36,100	36,100	36,100	36,100	36,100	36,100
$R^2$	0.004	0.889	0.891	0.921	0.004	0.872	0.891	0.898
<i>Additional controls:</i>								
Country fixed effects	No	Yes	Yes	No	No	Yes	Yes	No
Month dummies (aggregate seasonality)	No	No	Yes	No	No	No	Yes	No
Country X month interactions (local seasonality)	No	No	No	Yes	No	No	No	Yes

**Table 5: The spread of COVID-19 cases or lockdowns and change in finance mobile app adoption, by global region**

This table presents coefficient estimates for a panel regression model estimating the region-level relationship between the spread of COVID-19 on absolute number of downloads and relative (logarithmic) number of downloads for finance category mobile apps. We use a 14-day leading moving average to calculate downloads to smooth day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given region saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. Europe serves as the base category. Depending on the model specification, we include region fixed effects, month dummies to control for aggregate level seasonality in finance app downloads, and region X month interaction dummies to control for regional seasonality. Standard errors are clustered at the region level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, and Kaggle.

	DV=Absolute # of daily app downloads (in 1,000's)				DV=Relative (ln) of # daily app downloads			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Post-Confirmed case</i>	55.20*	-22.44			0.23**	0.16*		
	(0.018)	(0.245)			(0.002)	(0.049)		
<i>Post-Confirmed case</i> X Africa	-55.13*	112.13***			0.18*	0.39***		
	(0.041)	(0.000)			(0.036)	(0.000)		
<i>Post-Confirmed case</i> X Asia	1,871.80***	2,604.00***			0.69***	1.10***		
	(0.000)	(0.000)			(0.000)	(0.000)		
<i>Post-Confirmed case</i> X Middle East	75.99**	162.87***			0.22*	0.31**		
	(0.003)	(0.000)			(0.019)	(0.001)		
<i>Post-Confirmed case</i> X North America	1,858.95***	1,778.11***			0.85***	0.85***		
	(0.000)	(0.000)			(0.000)	(0.000)		
<i>Post-Confirmed case</i> X Oceania	221.28***	292.28***			0.29**	0.35***		
	(0.000)	(0.000)			(0.002)	(0.001)		
<i>Post-Confirmed case</i> X South America	307.93***	593.70***			0.06	0.15		
	(0.000)	(0.000)			(0.547)	(0.084)		
<i>Post-Lockdown</i>			3.79	-36.21***			0.04	-0.02***
			(0.868)	(0.000)			(0.455)	(0.000)
<i>Post-Lockdown</i> X Africa			9.45	100.73***			0.25***	0.43***
			(0.620)	(0.000)			(0.000)	(0.000)
<i>Post-Lockdown</i> X Asia			1,896.57***	2,326.09***			0.44***	0.65***
			(0.000)	(0.000)			(0.000)	(0.000)
<i>Post-Lockdown</i> X Middle East			99.91***	195.56***			0.32***	0.44***
			(0.000)	(0.000)			(0.000)	(0.000)
<i>Post-Lockdown</i> X North America			2,369.55***	2,178.99***			0.97***	0.91***
			(0.000)	(0.000)			(0.000)	(0.000)
<i>Post-Lockdown</i> X Oceania			256.05***	295.97***			0.35***	0.36***
			(0.000)	(0.000)			(0.000)	(0.000)
<i>Post-Lockdown</i> X South America			434.24***	611.74***			0.22**	0.33***
			(0.000)	(0.000)			(0.008)	(0.000)
Observations	3,325	3,325	3,325	3,325	3,325	3,325	3,325	3,325
$R^2$	0.941	0.961	0.932	0.947	0.595	0.602	0.583	0.587
<i>Additional controls:</i>								
Region fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Month dummies (aggregate seasonality)	Yes	No	Yes	No	Yes	No	Yes	No
Region X month interactions (local seasonality)	No	Yes	No	Yes	No	Yes	No	Yes

**Table 6: COVID-19 cases and change in fintech mobile app adoption, country-level characteristics predicting differential results**

This table presents coefficient estimates for a panel regression model estimating the country-level relationship between the spread of COVID-19 on absolute number of daily downloads and relative (logarithmic) number of daily downloads for finance category mobile apps. We use a 14-day leading moving average to calculate downloads to smooth day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given country saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. All models include country X month interaction dummies to control for country-level seasonality. Standard errors are clustered at the country level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, Kaggle, and WDI.

	DV=Absolute # of daily app downloads (in 1,000's)					DV=Relative (ln) of # daily app downloads				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Post-Confirmed case</i>	930.370 (0.296)	-1,662.417* (0.039)	192.626 (0.079)	269.632 (0.161)	103.992 (0.073)	1.065 (0.074)	-1.332*** (0.000)	0.514*** (0.000)	0.247 (0.111)	0.285*** (0.000)
<i>Post-Confirmed case</i> X ln(GDP per capita)	-82.075 (0.336)					-0.072 (0.217)				
<i>Post-Confirmed case</i> X ln(Country population)		102.518* (0.036)					0.097*** (0.000)			
<i>Post-Confirmed case</i> X % Pop. aged 65 and up			-7.434 (0.210)					-0.014 (0.051)		
<i>Post-Confirmed case</i> X % Pop. w/ mobile subscription				-1.388 (0.269)					0.001 (0.593)	
<i>Post-Confirmed case</i> X % Pop. ex-ante receiving wages via mobile phone					-1.246 (0.693)					0.006 (0.312)
Observations	32,775	32,775	33,250	32,775	32,300	33,250	33,725	34,200	33,725	33,250
$R^2$	0.924	0.932	0.923	0.923	0.922	0.891	0.891	0.889	0.890	0.886
<i>Additional controls:</i>										
Country X month interactions (local seasonality)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

**Table 7: COVID-19 lockdowns and change in fintech mobile app adoption, country-level characteristics predicting differential results**

This table presents coefficient estimates for a panel regression model estimating the country-level relationship between the spread of COVID-19 on absolute number of daily downloads and relative (logarithmic) number of daily downloads for finance category mobile apps. We use a 14-day leading moving average to calculate downloads to smooth day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given country saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. All models include country X month interaction dummies to control for country-level seasonality. Standard errors are clustered at the country level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, Kaggle, and WDI.

	DV=Absolute # of daily app downloads (in 1,000's)					DV=Relative (ln) of # daily app downloads				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Post-Lockdown</i>	716.814 (0.329)	-1,335.540 (0.066)	166.995 (0.063)	273.522 (0.230)	100.859* (0.047)	1.017 (0.098)	-0.978* (0.025)	0.493*** (0.000)	0.216 (0.344)	0.256*** (0.000)
<i>Post-Lockdown</i> X ln(GDP per capita)	-62.427 (0.378)					-0.074 (0.216)				
<i>Post-Lockdown</i> X ln(Country population)		83.432 (0.062)					0.073** (0.006)			
<i>Post-Lockdown</i> X % Pop. aged 65 and up			-6.404 (0.187)					-0.018** (0.005)		
<i>Post-Lockdown</i> X % Pop. w/ mobile subscription				-1.563 (0.346)					0.000 (0.874)	
<i>Post-Lockdown</i> X % Pop. ex-ante receiving wages via mobile phone					-2.404 (0.296)					-0.002 (0.705)
Observations	32,775	32,775	33,250	32,775	32,300	33,250	33,725	34,200	33,725	33,250
$R^2$	0.921	0.925	0.921	0.921	0.920	0.890	0.889	0.888	0.889	0.884
<i>Additional controls:</i>										
Country X month interactions (local seasonality)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes



## A Appendix

### A.1 Data sample

**Table A.1: Overview of countries in data sample**

This table lists the 74 countries for which we have mobile app download data along with their region, date of first confirmed case of COVID-19, and date of lockdown (if applicable). Data sources: AppTweak, OxGCRT, and Kaggle.

Country	Country Code	Region	1st COVID-19 case	Lockdown startdate
Algeria	DZA	Africa	2 Mar 2020	24 Mar 2020
Argentina	ARG	South America	6 Mar 2020	20 Mar 2020
Australia	AUS	Oceania	26 Jan 2020	24 Mar 2020
Austria	AUT	Europe	26 Feb 2020	16 Mar 2020
Belarus	BLR	Europe	–	–
Belgium	BEL	Europe	2 Mar 2020	17 Mar 2020
Brazil	BRA	South America	1 Mar 2020	–
Bulgaria	BGR	Europe	8 Mar 2020	13 Mar 2020
Canada	CAN	North America	28 Jan 2020	12 Mar 2020
Chile	CHL	South America	5 Mar 2020	26 Mar 2020
China	CHN	Asia	1 Dec 2019	23 Jan 2020
Colombia	COL	South America	10 Mar 2020	25 Mar 2020
Croatia	HRV	Europe	27 Feb 2020	22 Mar 2020
Czech Republic	CZE	Europe	2 Mar 2020	16 Mar 2020
Denmark	DNK	Europe	29 Feb 2020	11 Mar 2020
Ecuador	ECU	South America	2 Mar 2020	24 Mar 2020
Egypt	EGY	Middle East	2 Mar 2020	24 Mar 2020
Estonia	EST	Europe	4 Mar 2020	13 Mar 2020
Finland	FIN	Europe	27 Feb 2020	27 Mar 2020
France	FRA	Europe	25 Jan 2020	16 Mar 2020
Germany	DEU	Europe	29 Jan 2020	20 Mar 2020
Greece	GRC	Europe	28 Feb 2020	18 Mar 2020
Hong Kong	HKG	Asia	23 Jan 2020	–
Hungary	HUN	Europe	5 Mar 2020	16 Mar 2020
Iceland	ISL	Europe	2 Mar 2020	16 Mar 2020
India	IND	Asia	2 Feb 2020	24 Mar 2020
Indonesia	IDN	Oceania	2 Mar 2020	15 Mar 2020
Ireland	IRL	Europe	4 Mar 2020	12 Mar 2020
Israel	ISR	Middle East	24 Feb 2020	12 Mar 2020
Italy	ITA	Europe	31 Jan 2020	11 Mar 2020
Japan	JPN	Asia	24 Jan 2020	27 Feb 2020
Jordan	JOR	Middle East	16 Mar 2020	21 Mar 2020
Kazakhstan	KAZ	Asia	15 Mar 2020	15 Mar 2020
Kuwait	KWT	Middle East	24 Feb 2020	16 Mar 2020
Lebanon	LBN	Middle East	27 Feb 2020	16 Mar 2020

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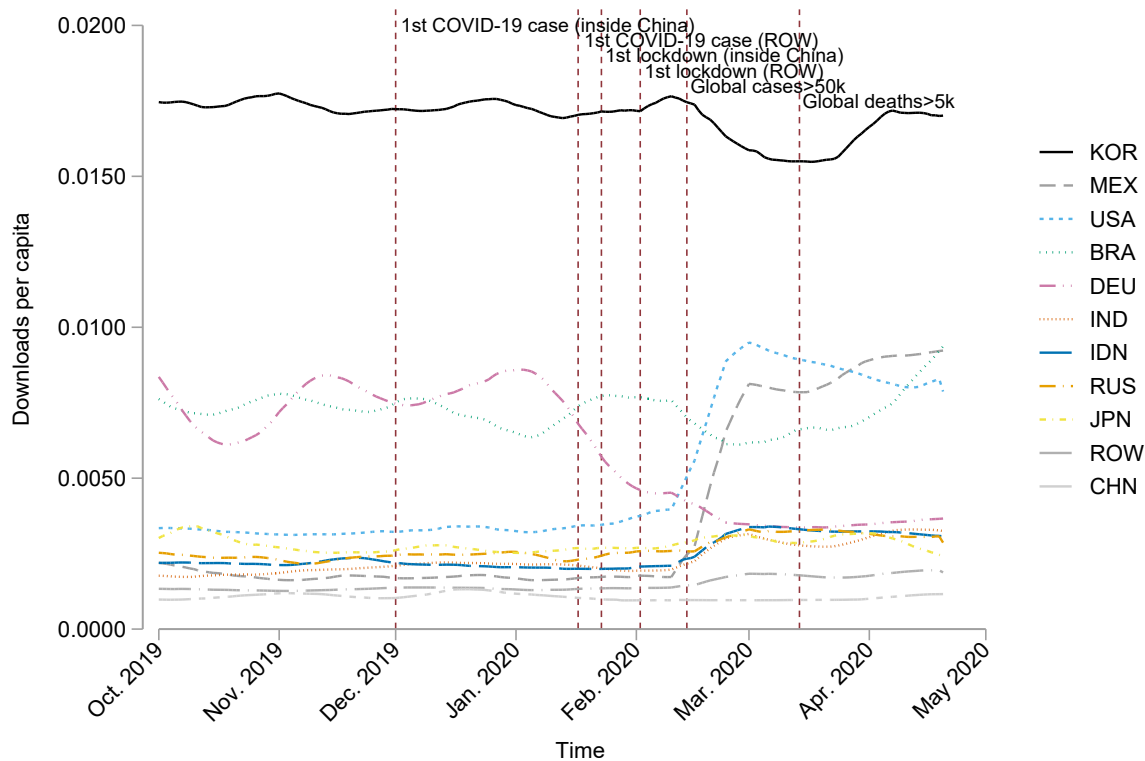
<b>Country</b>	<b>Country Code</b>	<b>Region</b>	<b>1st COVID-19 case</b>	<b>Lockdown startdate</b>
Lithuania	LTU	Europe	–	16 Mar 2020
Luxembourg	LUX	Europe	7 Mar 2020	16 Mar 2020
Macao	MAC	Asia	23 Jan 2020	–
Malaysia	MYS	Asia	25 Jan 2020	18 Mar 2020
Mexico	MEX	North America	29 Feb 2020	14 Mar 2020
Netherlands	NLD	Europe	29 Feb 2020	16 Mar 2020
New Zealand	NZL	Oceania	4 Mar 2020	25 Mar 2020
Nigeria	NGA	Africa	10 Mar 2020	25 Mar 2020
Norway	NOR	Europe	28 Feb 2020	12 Mar 2020
Oman	OMN	Middle East	25 Feb 2020	29 Mar 2020
Pakistan	PAK	Asia	27 Feb 2020	26 Mar 2020
Peru	PER	South America	9 Mar 2020	10 Mar 2020
Philippines	PHL	Asia	2 Feb 2020	16 Mar 2020
Poland	POL	Europe	7 Mar 2020	12 Mar 2020
Portugal	PRT	Europe	3 Mar 2020	18 Mar 2020
Qatar	QAT	Middle East	2 Mar 2020	11 Mar 2020
Romania	ROU	Europe	29 Feb 2020	25 Mar 2020
Russia	RUS	Europe	1 Feb 2020	27 Mar 2020
Saudi Arabia	SAU	Middle East	6 Mar 2020	15 Mar 2020
Serbia	SRB	Europe	11 Mar 2020	15 Mar 2020
Singapore	SGP	Asia	24 Jan 2020	26 Mar 2020
Slovak Republic	SVK	Europe	8 Mar 2020	–
Slovenia	SVN	Europe	6 Mar 2020	11 Mar 2020
South Africa	ZAF	Africa	8 Mar 2020	26 Mar 2020
South Korea	KOR	Asia	24 Jan 2020	23 Feb 2020
Spain	ESP	Europe	10 Feb 2020	14 Mar 2020
Sweden	SWE	Europe	27 Feb 2020	–
Switzerland	CHE	Europe	28 Feb 2020	18 Mar 2020
Thailand	THA	Asia	17 Jan 2020	22 Mar 2020
Tunisia	TUN	Middle East	10 Mar 2020	20 Mar 2020
Turkey	TUR	Middle East	13 Mar 2020	23 Mar 2020
Ukraine	UKR	Europe	13 Mar 2020	17 Mar 2020
United Arab Emirates	ARE	Middle East	30 Jan 2020	24 Mar 2020
United Kingdom	GBR	Europe	31 Jan 2020	18 Mar 2020
United States	USA	North America	25 Jan 2020	13 Mar 2020
Uruguay	URY	South America	15 Mar 2020	16 Mar 2020
Venezuela	VEN	South America	15 Mar 2020	16 Mar 2020
Vietnam	VNM	Asia	24 Jan 2020	19 Mar 2020
Zimbabwe	ZWE	Africa	22 Mar 2020	27 Mar 2020

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## A.2 Additional figures

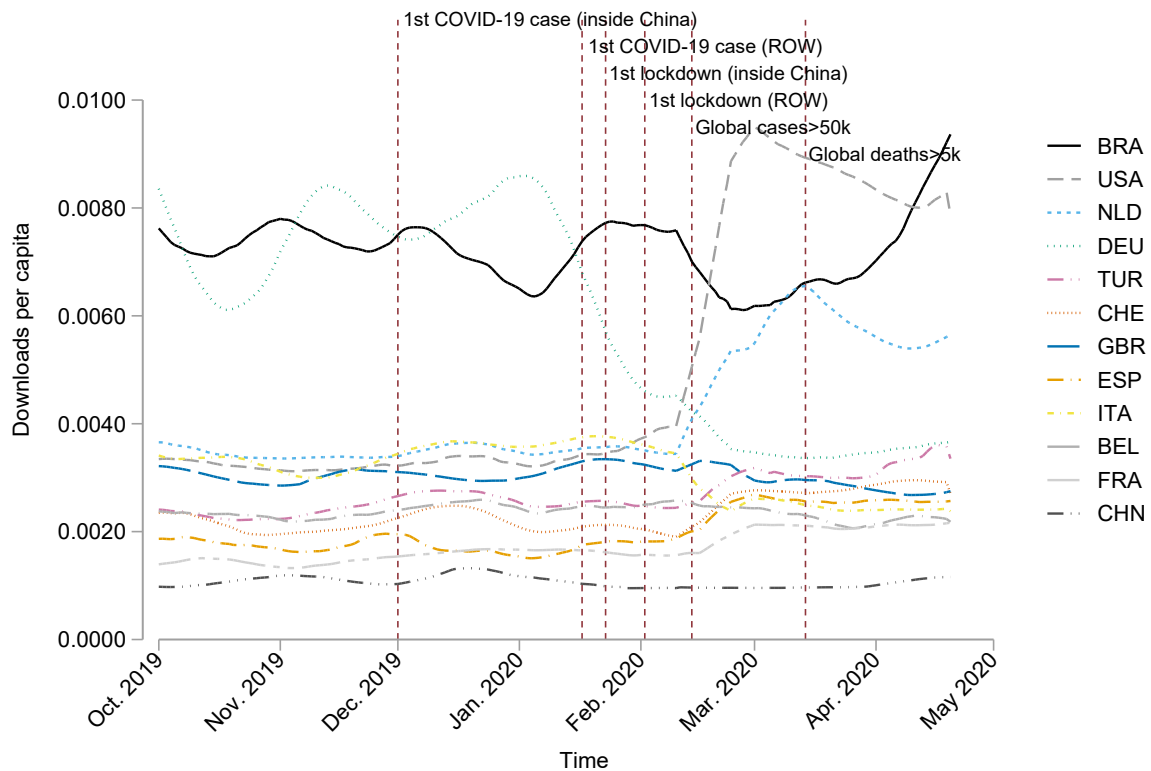
**Figure 3: Daily rate of downloads per capita for finance category mobile apps across 10 largest country markets**

This figure depicts the daily rate of downloads per capita for finance category mobile applications from the top 10 country markets (Brazil, China, Germany, India, Indonesia, Japan, Mexico, Russia, South Korea, and the United States) and the “rest of the world” (ROW). Country codes are listed in Appendix Table A.1. The data includes mobile apps from both the iOS and Android platforms from October 1st, 2019 to April 20th, 2020. We calculate a 14-day leading moving average on downloads to smooth day-to-day fluctuations.



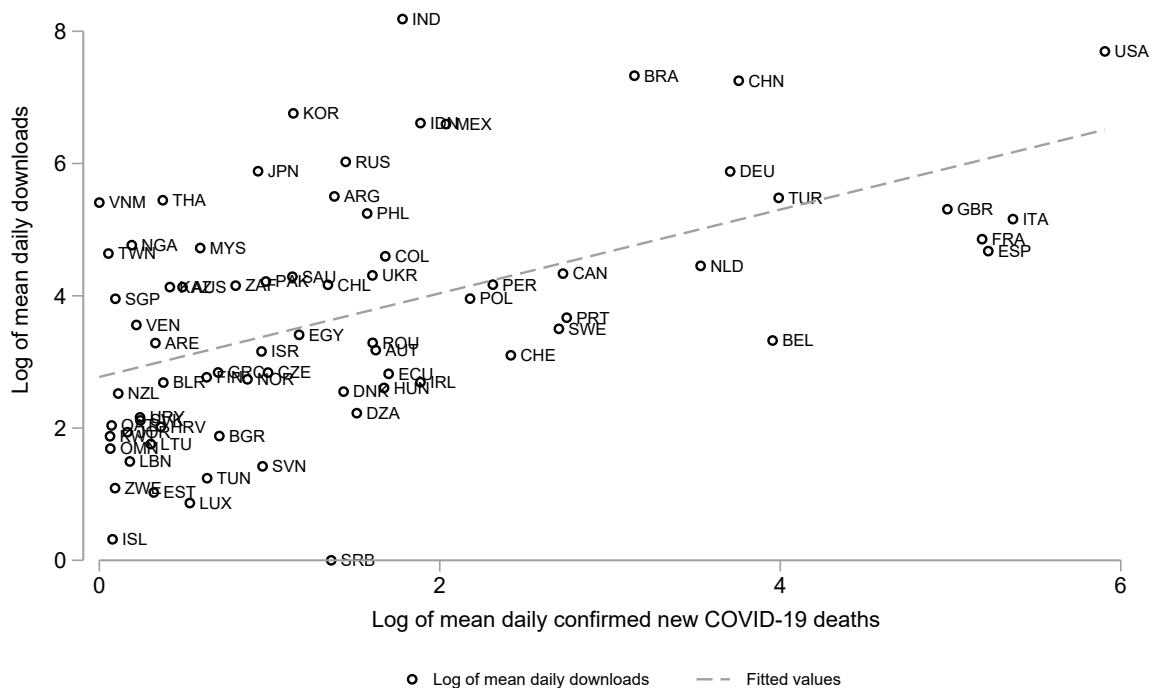
**Figure 4: Daily rate of downloads per capita for finance category mobile apps across countries most affected by COVID-19**

This figure depicts the daily rate of downloads per capita for finance category mobile applications for countries with the most confirmed cases of COVID-19 (Belgium, China, France, Germany, Italy, the Netherlands, Spain, Switzerland, United Kingdom, and the United States). Country codes are listed in Appendix Table A.1. The data includes mobile apps from both the iOS and Android platforms from October 1st, 2019 to April 20th, 2020. We calculate a 14-day leading moving average on downloads to smooth day-to-day fluctuations.



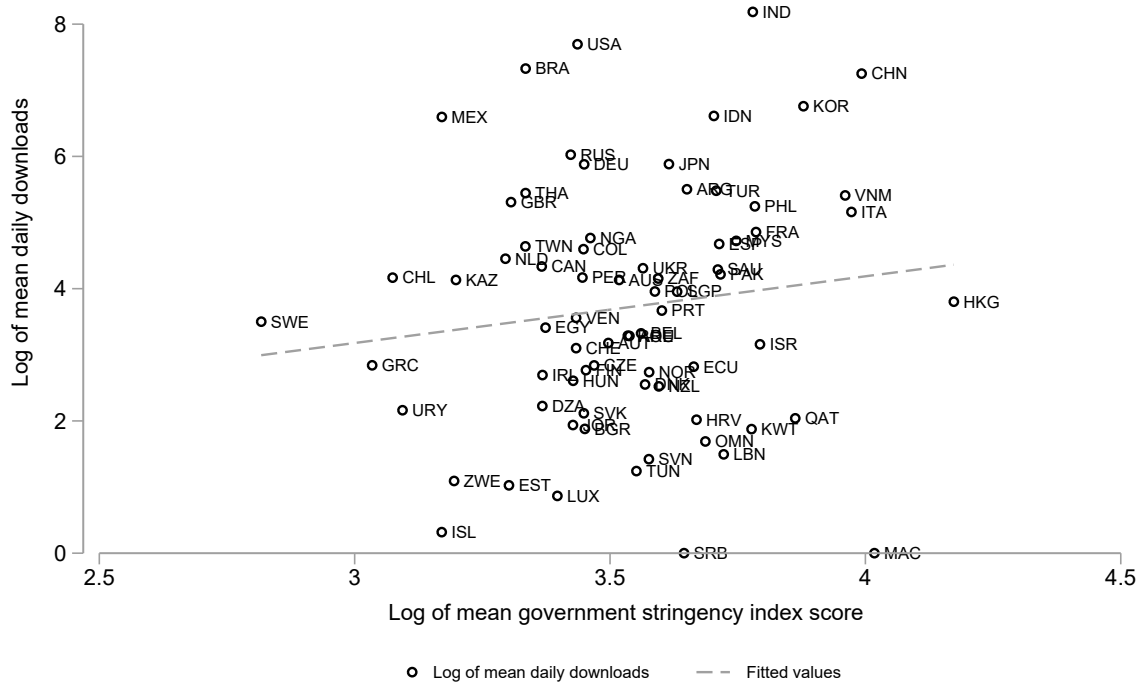
**Figure 5: Scatterplot of Finance Category Mobile App Downloads vs. Confirmed COVID-19 Deaths**

This figure depicts the relationship between average daily number of downloads for finance category mobile applications and average daily confirmed new deaths of COVID-19. We roughly restrict to the general period after the first signs of the COVID-19 outbreak (i.e., since January 1st, 2020). The underlying data includes mobile apps from both the iOS and Android platforms for 74 countries. Country codes are listed in Appendix Table A.1. Data sources: AppTweak and OxCGRT.



**Figure 6: Scatterplot of Finance Category Mobile App Downloads vs. Government Policy Stringency Index**

This figure depicts the relationship between average daily number of downloads for finance category mobile applications and average daily government stringency index score. Specifically, the Oxford COVID-19 Government Response Tracker (OxCGRT) systematically collects information on several different common policy responses governments have taken to mitigate COVID-19, scores the stringency of such measures, and aggregates these scores into a common Stringency Index. We roughly restrict to the general period after the first signs of the COVID-19 outbreak (i.e., since January 1st, 2020). The underlying data includes mobile apps from both the iOS and Android platforms for 74 countries. Country codes are listed in Appendix Table A.1. Data sources: AppTweak and OxCGRT.



### A.3 Sensitivity tests on use of moving averages for estimating change in downloads

We test how sensitive our main results are to the use of different windows for calculating moving averages for downloads. We rerun main results for specifications 4 and 8 from Tables 3 and 4 using the original number of downloads versus a 10-day moving average, 14-day moving average, 20-day moving average, and 30-day moving average.

Tables A.2 and A.3 present results from this sensitivity analysis. In general, we do observe that the economic size and statistical significance of the effects tend to grow incrementally as we increase the window for the moving average. This is most notable when using the *Post-Confirmed case* variable for models estimating relative change in downloads. That having been said, the main trends and results are fairly consistent regardless of explanatory variable used or dependent variable construction. We imagine the original and 30-day moving average results provide an lower and upper-bound, respectively. Thus, in our main analysis, we use the 14-day moving average results to provide a middle ground estimate.

**Table A.2: Sensitivity tests on construction of main DV, post-confirmed case**

This table presents coefficient estimates for a panel regression model estimating the country-level relationship between the spread of COVID-19 on absolute number of daily downloads and relative (logarithmic) number of daily downloads for finance category mobile apps. We rerun specifications 4 and 8 from Table 3 using original download numbers and then when calculating the moving average using a 10-day (10DMA), 14-day (14DMA), 20-day (20DMA), and 30-day (30DMA) leading window. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given country saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. Standard errors are clustered at the country level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, and Kaggle.

	DV=Absolute # of daily app downloads (in 1,000's)					DV=Relative (ln) of # daily app downloads				
	Original	10DMA	14DMA	20DMA	30DMA	Original	10DMA	14DMA	20DMA	30DMA
<i>Post-Confirmed case</i>	87.418*	87.625*	87.745*	88.106*	89.473*	0.251***	0.297***	0.316***	0.345***	0.395***
	(0.047)	(0.037)	(0.033)	(0.028)	(0.020)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	36,100	36,100	36,100	36,100	36,100	36,100	36,100	36,100	36,100	36,100
$R^2$	0.937	0.927	0.923	0.918	0.914	0.993	0.921	0.899	0.876	0.861
<i>Additional controls:</i>										
Country X month interactions (local seasonality)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes





#### A.4 Results in terms of change in rate of daily downloads per capita

We alternatively calculate and present results in terms of the daily rate of downloads per capita. Across the 74 countries in our dataset, we observe a daily average of roughly 0.00195 downloads per capita in the period roughly prior to the advance of COVID-19 (i.e., in 2019). For the roughly 6 billion individuals covered in our country sample, this translates into an average of 11.7 million finance category app downloads daily from the Android and iOS platforms in the pre-COVID-19 period.

Table A.4 presents the comparable per capita-adjusted results for Tables 3 and 4. We observe that following the onset of confirmed COVID-19 cases or related lockdowns, the daily rate of downloads per capita increased by between 0.00066 and 0.00061—i.e., from roughly 0.00195 to between 0.00256 and 0.00261. Again taking into consideration the full country sample population, this equates to increasing from 11.7 to between 15.2 and 15.6 million downloads a day.

Similarly, Table A.5 presents the comparable per capita-adjusted results for the region-level analysis in Table 5. At a high-level, we observe similar patterns to the results from our specifications using logarithmic form to measure our DV. However, whereas results from Table 5 show Asia and North America as seeing the largest increases in terms of absolute terms, the per capita results emphasize that the magnitude of increase in North America and South America was particularly large, adjusting for countries' population size. European countries again show signs of a decrease in daily downloads per capita.

**Table A.4: The spread of COVID-19 government lockdown and daily finance mobile app downloads per capita**

This table presents coefficient estimates for a panel regression model estimating the country-level relationship between the spread of COVID-19 on the daily number of finance category mobile app downloads per capita. We use a 14-day leading moving average to calculate downloads to smooth some day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given country saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. Depending on the model specification, we include country fixed effects, month dummies to control for aggregate level seasonality in finance app downloads, and country X month interaction dummies to control for country-level seasonality. Standard errors are clustered at the country level. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, and Kaggle.

	DV=# of daily app downloads per capita							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Post-Confirmed case</i>	0.00100*** (0.000)	0.00065*** (0.000)	0.00061*** (0.000)	0.00066*** (0.000)				
<i>Post-Lockdown</i>					0.00077** (0.002)	0.00068*** (0.000)	0.00057*** (0.001)	0.00061*** (0.000)
Observations	36,100	36,100	36,100	36,100	36,100	36,100	36,100	36,100
$R^2$	0.020	0.895	0.900	0.924	0.007	0.892	0.897	0.921
<i>Additional controls:</i>								
Country fixed effects	No	Yes	Yes	No	No	Yes	Yes	No
Month dummies (aggregate seasonality)	No	No	Yes	No	No	No	Yes	No
Country X month interactions (local seasonality)	No	No	No	Yes	No	No	No	Yes

**Table A.5: The spread of COVID-19 cases or lockdowns and daily finance mobile app downloads per capita, by global region**

This table presents coefficient estimates for a panel regression model estimating the region-level relationship between the spread of COVID-19 on the daily number of download per capita for finance category mobile apps. We use a 14-day leading moving average to calculate downloads to smooth day-to-day fluctuations. *Post-Confirmed case* and *Post-Lockdown* denote dummy indicators that are turned on after a given region saw its first confirmed COVID-19 case or its government-initiated lockdown, respectively. The data sample covers the full iOS and Android mobile app markets for 74 countries daily from January 1st, 2019 to April 20th, 2020. Depending on the model specification, we include region fixed effects, month dummies to control for aggregate level seasonality in finance app downloads, and region X month interaction dummies to control for regional seasonality. Standard errors are clustered at the region level. Europe serves as the base region. *p*-values in parentheses \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.5$ . Data sources: AppTweak, OxCGRT, and Kaggle.

	DV=# of daily app downloads per capita			
	(1)	(2)	(3)	(4)
<i>Post-Confirmed case</i>	0.00006 (0.079)	-0.00003 (0.245)		
<i>Post-Confirmed case</i> X Africa	0.00005 (0.202)	0.00032*** (0.000)		
<i>Post-Confirmed case</i> X Asia	0.00060*** (0.000)	0.00077*** (0.000)		
<i>Post-Confirmed case</i> X Middle East	0.00039*** (0.000)	0.00055*** (0.000)		
<i>Post-Confirmed case</i> X North America	0.00380*** (0.000)	0.00361*** (0.000)		
<i>Post-Confirmed case</i> X Oceania	0.00082*** (0.000)	0.00094*** (0.000)		
<i>Post-Confirmed case</i> X South America	0.00090*** (0.000)	0.00146*** (0.000)		
<i>Post-Lockdown</i>			-0.00002 (0.573)	-0.00005*** (0.000)
<i>Post-Lockdown</i> X Africa			0.00014*** (0.000)	0.00026*** (0.000)
<i>Post-Lockdown</i> X Asia			0.00046*** (0.000)	0.00071*** (0.000)
<i>Post-Lockdown</i> X Middle East			0.00049*** (0.000)	0.00064*** (0.000)
<i>Post-Lockdown</i> X North America			0.00487*** (0.000)	0.00442*** (0.000)
<i>Post-Lockdown</i> X Oceania			0.00097*** (0.000)	0.00093*** (0.000)
<i>Post-Lockdown</i> X South America			0.00114*** (0.000)	0.00149*** (0.000)
Observations	3,325	3,325	3,325	3,325
$R^2$	0.870	0.893	0.835	0.864
<i>Additional controls:</i>				
Region fixed effects	Yes	No	Yes	No
Month dummies (aggregate seasonality)	Yes	No	Yes	No
Region X month interactions (local seasonality)	No	Yes	No	Yes

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c/o University of Geneva, Bd. Du Pont d'Arve 42, CH-1211 Geneva 4  
T +41 22 379 84 71, rps@sfi.ch, www.sfi.ch