The Death of Distance? COVID-19 Lockdowns and Venture Capital Investment*

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Abstract

Based on 4,086 venture capital (VC) firms in 49 countries accounting for 90.0% of global GDP, we study how COVID-19 lockdowns affect VC investment decisions. Contrary to the conventional wisdom that lockdowns exacerbate the "tyranny of distance," our findings suggest the "death of distance": VCs invest in more distant ventures during the COVID-19 pandemic in 2020 and such effects persisted and accelerated in 2021. The death of distance in VC investment is more pronounced when there is better internet infrastructure, when the level of information asymmetry between VCs and entrepreneurs is lower, and when the deal size is smaller. The pandemic-spurred advancement and adoption of remote communication technology have contributed to the death of distance in VC investment. As geographic boundaries of VC investment are shattered after the pandemic, local competition among the VCs has intensified and the regional inequality of entrepreneurial access to VC financing has been mitigated.

Keywords: Venture Capital, Entrepreneurship, COVID-19, Pandemic, Lockdown, Digitalization
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1 Introduction

"Let's not pretend that things will change if we keep doing the same things. A crisis can be a real blessing to any person, to any nation. For all crises bring progress. Creativity is born from anguish. Just like the day is born from the dark night. It's in crisis that inventive is born, as well as discoveries, and big strategies."

Albert Einstein

To contain the spread of the COVID-19 pandemic, various government restriction policies on human mobility (known as lockdowns, shelter-in-place or stay-at-home orders, etc.) have been adopted all around the world. By the end of 2021, 99.0% of the world population has experienced international travel restrictions, 95.5% has experienced domestic travel restrictions, 98.4% has experienced school closings, 88.7% has experienced workplace closings, 77.2% has experienced public transport closings, and 60.5% has experienced stay-at-home requirements.[1] Such mobility restriction policies have posed unprecedented and acute challenges to a myriad of economic activities. Nevertheless, a crisis constitutes a mixed blessing in the sense that it could spur reforms and breed progress, as underscored by Albert Einstein and demonstrated by significant historic events such as the Great Depression and the Great Recession. In the aftermath of the COVID-19 crisis, what changes have been made to address the disruptions of the "Great Lockdown"?[2] Will the Great Lockdown resemble the reform-promoting role of the Great Depression and the Great Recession?

To investigate these questions, we study how COVID-19 lockdowns affect the investment decisions of venture capital (VC) investors. The reason for us to focus on VC investors is threefold. First, the VC investment process has been severely disrupted by COVID-19 lockdowns because on-site visits and in-person meetings are of paramount importance in the VC industry (Sahlman (1990)). Second, VC investors have strong incentives to swiftly adapt to lockdowns and they are flexible to initiate organizational reforms. As the general partners under the limited partnership arrangement, VC firms are under hefty pressure to deliver large financial returns within a certain period. Thus, VC firms have strong incentives to promptly adapt their investment process to the COVID-19 mobility restrictions. Since a VC firm typically comprises a small number of partners,

[1] Source: Oxford COVID-19 Government Response Tracker.

[2] The term "Great Lockdown" was coined by the International Monetary Fund (IMF) in 2020. See the IMF report on "The Great Lockdown: Worst Economic Downturn since the Great Depression," April 14, 2020.

it is relatively agile to initiate organizational reforms, compared to large financial institutions such as commercial and investment banks.[3] Third, comprehensive and elaborate information on VC investments is available in real-time, allowing us to track how VC investment decisions changed during the COVID-19 lockdowns and after the economy reopened.

Based on deal-level evidence of 4,086 venture capital (VC) firms in 49 countries accounting for 90.0% of global GDP, our empirical investigations have delivered striking results. As underscored in Petersen and Rajan (2002), investing in private small ventures is challenging because there is a dearth of public information for such businesses and such information tends to be "soft" (Stein (2002)). To gather information about such private small businesses and monitor the startups, direct contact with the entrepreneurs is of paramount importance and, thus, the investment decisions of VCs hinge critically on the costs of communicating with the entrepreneurs and monitoring the ventures. The vital role of geographic proximity and local presence (e.g., Lerner (1995), Tian (2011)) and on-site visits (e.g., Sahlman (1990)) in the VC industry has been well documented in the literature. Since visiting startup companies in remote areas becomes substantially more difficult under lockdowns, conventional wisdom suggests VC investors tend to invest in local instead of remote ventures, and, thus, aggravating the "tyranny of distance." Contrary to conventional wisdom, however, our findings suggest the "death of distance" (i.e., VCs invest in more distant ventures): A VC firm invests in startup companies that are 11.4% (about 123 kilometers) farther away in 2020, compared to the investments made by the same VC firm in 2017 (the omitted group in the regressions). In addition, the symptom of increasing VC-startup distance is more pronounced in countries with more stringent government restrictions on human mobility.[4] Moreover, such an increase in VC-startup distance has further expanded to 29.7% (about 320 kilometers) in 2021. While the post-pandemic period has not been long enough to reach any solid conclusions, the persistence and acceleration of the death of distance in 2021 constitute early suggestive evidence that the changes in VC investment strategies during the Great Lockdown may herald long-lasting

[3]According to the 2015 yearbook of the National Venture Capital Association, the average VC firm has about seven principals (i.e., deal partners attending board meetings of the portfolio companies).

[4]For instance, consider a comparison between the United States and China, two nations with salient differences in their approaches to combat the COVID-19 pandemic. Compared to the situation in 2017 (the omitted group in the regressions), VC-startup distance in 2020 has ratcheted up by 9.4% (about 101 kilometers) in the United States, whereas this number is 21.5% (about 232 kilometers) in China.

transformations in the post-pandemic "new normal."

While our findings based on global VC investments indicate that the death of distance constitutes a global phenomenon, one may be concerned that these findings could be driven by country-level unobservables. Parallel to our study based on global VC investments, we alleviate the concern for country-level unobservables by probing the effects of COVID-19 lockdowns in one country–China. We focus on China because it is the first country to be severely hit by the COVID-19 pandemic. China is also the first country to impose drastic restrictions (such as lockdowns and face mask mandates) to contain the spread of COVID-19 and its restriction policies are among the most stringent in the world. To the extent that China's experience constitutes a precedent for other countries that were subsequently stricken by COVID-19, the pandemic is more eligible to be an *unanticipated* shock in the Chinese context. Exploiting the regional differences in lockdowns and reopening in China, we adopt two lockdown proxies (one based on the government lockdown mandate and another one based on the actual human mobility level) and we distinguish between different phases of lockdowns and reopening to sharpen our analysis. Echoing our findings based on global VC investments, the death of distance is also manifested in the Chinese context: VCs in China invest in more distant ventures during the COVID-19 lockdowns and the effects persist after the economy reopens.

Since the VC decisions to invest in local versus remote ventures hinge crucially on the costs of communicating with the entrepreneurs and monitoring the ventures, the pandemic-spurred advancement and adoption of remote communication technology emerge as a contributing factor to the death of distance in VC investment. Digital technologies (e.g., the 5G technology, artificial intelligence, big data, cloud computing, and the internet of things) have been of vital importance in combating COVID-19 and maintaining business operations despite the pandemic disruptions. In particular, a myriad of technological innovations for remote communication has been swiftly created and widely adopted to address the pandemic-induced social distancing requirements. As a response, many VC investors have seized this technological opportunity and transformed their traditional in-person meetings into online conferences. For instance, Sequoia Capital China introduced its first "Online Demo Day" as early as February 18, 2020, and it was widely applauded by both the startups and the investors. In light of this, enhanced remote communication technology has reduced the costs of communicating with entrepreneurs and monitoring their businesses and, thus, incentivizes the VCs to invest in more distant ventures.

We find consistent evidence that enhanced remote communication technology has contributed to the death of distance in VC investment. We exploit the heterogeneity of VCs and startups along three dimensions: (i) internet infrastructure, (ii) information asymmetry between VCs and entrepreneurs, and (iii) deal size. We find that the death of distance in VC investment is more salient in cities with better internet infrastructure, in industries featuring a lower level of information asymmetry between VCs and entrepreneurs, and in deals where the VCs invest a smaller amount of money.[5] These empirical findings provide supporting evidence that remote communication technology has contributed to the death of distance in VC investment.

The death of distance in VC investment has two major implications on entrepreneurial finance. First, we find that local competition among the VCs has intensified after the pandemic. Since there is a paucity of public information about private small ventures, local presence or on-site visits are essential for the investors to acquire information of the entrepreneurs and monitor their businesses. In light of this, a VC investor features monopoly power in its local market because it enjoys lower travel and monitoring costs than other competing VCs located far away from the startups. In small business financing, it is well-documented that local investors wield their market power to extract spatial rents from local businesses.[6] As geographic boundaries of VC investment are shattered after the pandemic, we find that the influx of investors from outside regions has intensified local competition among the VCs. In the aftermath of the COVID-19 pandemic, a startup company is more likely to receive financing from foreign VCs and distant VCs (e.g., those located more than 1,000 kilometers away). Based on the Herfindahl-Hirschman index (HHI) of VC investments received by startups in each city (a proxy of the concentration of the source of VC financing), we find that local competition among the VCs has intensified. Such heightened competition among

[5]While a brief virtual meeting may be well enough for deals with a tiny amount of investments, in-person meetings could still be essential for crucial deals with hefty financial commitment from the VCs. As consistent evidence, we find that the death of distance in VC investment is more pronounced when the deal size is smaller.

[6]For instance, such spatial rents can be extracted by spatial price discrimination as documented in Degryse and Ongena (2005).

the VCs may contribute to curtailing their monopoly power and eroding their spatial rents.

As the second implication of the death of distance in VC investment, we find that the regional inequality of entrepreneurial access to VC financing has been mitigated. VC investment features a high level of geographic concentration (Chen et al. (2010)). Since most VCs are located in economically advanced regions, the regional inequality of entrepreneurial access to VC financing is in part due to the time and financial costs of long-distance travel. In light of our previous findings on the death of distance in VC investment, one may wonder if the regional inequality of VC financing will be mechanically alleviated as VC funding shifts toward remoter ventures after the pandemic. This is not necessarily true because the death of distance can be also attributed to a reshuffling of VC financing among the economically advanced regions.[7] Does the death of distance imply that more VC funding has been channeled toward entrepreneurs in disadvantaged regions? Our findings have yielded a positive answer. We find that the geographic distribution of VC investments in a country has become more dispersed after the COVID-19 pandemic. In addition, VCs are significantly more likely to invest in startups in economically disadvantaged regions in the post-pandemic era.[8] Therefore, removing the geographic barriers to VC investment mitigates the regional inequality of entrepreneurial access to VC financing and democratizes entrepreneurship. Viewed from this perspective, the COVID-19 pandemic is to some extent a paradoxical blessing instead of a curse for entrepreneurs in disadvantaged regions.

Our paper contributes to three strands of literature. The first one is a fast-growing body of literature on the COVID-19 pandemic, particularly the studies on lockdowns and the studies examining the impact of COVID-19 on the VC industry. Gompers et al. (2021) survey a large number of VC firms on how they have been affected by the COVID-19 pandemic. Howell et al. (2021) find that early-stage VC investment is more sensitive to market conditions than late-stage investment. Ozik et al. (2021) show that retail trading attenuates the increase in stock liquidity during the COVID-19 lockdowns in the United States. Barrios et al. (2021) find that regions

[7] That is to say, VCs in advanced regions may invest in local startups before COVID-19 and switch to remote startups in other *advanced* regions after the pandemic.

[8] We adopt three strategies to categorize an economically disadvantaged region in each country: (i) cities receiving fewer than three VC investments before the COVID-19 pandemic, (ii) the bottom 30% cities in a country ranked by VC investments received before the pandemic, (iii) the bottom 30 cities in a country ranked by VC investments received before the pandemic.

with higher civic capital featured a higher level of voluntary social distancing, both during the pandemic and after the economy started to reopen. Ding et al. (2021) document the relation between corporate characteristics and the reaction of stock returns to COVID-19 cases. Fang et al. (2020) quantify how human mobility restrictions contain the spread of COVID-19 in China. Liu et al. (2021) find that the government-issued digital coupon program in China is highly effective in stimulating consumption and a behavioral model with mental accounting and loss aversion can match the empirical evidence. We contribute to this literature by uncovering the death of distance in VC investment after the pandemic in a global context, as well as its implications on VC competition and the regional inequality of entrepreneurial access to VC financing.

Our paper is also related to the broader literature on small business financing, particularly the studies with a focus on geographic proximity between entrepreneurs and investors. Petersen and Rajan (2002) pioneer in documenting that the growing use of information technology in the U.S. led to increasing physical distance between small firms and their lenders, as well as less personal interaction in their communication. The findings in Petersen and Rajan (2002) are confirmed and enriched in subsequent studies (e.g., DeYoung et al. (2010)). The findings in these U.S.-based studies are strengthened and enriched in our research context. In the aftermath of the COVID-19 pandemic, we find that the death of distance in VC investment is a global phenomenon. In light of this, the impact of information technology on finance has transcended time, space (the U.S. vs a global phenomenon), different types of financial contracts (loans vs equity investment), and different types of financial institutions (banks vs VCs). In addition, we have also enriched the studies on geographic proximity by exploring its implications on entrepreneurial finance (i.e., intensified VC competition and mitigated regional inequality of VC financing).

Finally, our paper contributes to the studies on the role of geography in the VC industry. Lerner (1995) finds that distance to startup companies plays a key role in determining the board membership of the VC firms. Chen et al. (2010) document the geographic concentration of the VC industry and show that VC firms located in VC centers outperform. Tian (2011) finds that VCs located farther away finance startup companies with more financing rounds, shorter durations between successive rounds, and invest a smaller amount in each round. Exploiting the introduction of new airline routes, Bernstein et al. (2016) show that on-site visits of VCs enhance the performance of startup companies. Amornsiripanitch et al. (2019) find that the probability for a VC firm to take a board seat in a startup company is increasing in its geographical proximity to the startup. These studies are typically based on the U.S. experience, whereas we extend the analysis of the role of geography in the VC industry to a global setting. While these papers study how the distance or travel time to startup companies affects the VC investment decisions, our study explores how the VC-startup distance is determined in the first place (in the sense that we examine how the VCs decide to invest in startups at different distances from them) and probes its implications on entrepreneurial finance. Though many studies have underlined the crucial role of on-site visits and the local bias of the VCs, our findings suggest that the importance of such factors has paradoxically declined in the aftermath of the COVID-19 pandemic.

The rest of the paper is organized as follows. We document the death of distance based on global VC investments in Section 2. To sharpen our analysis, we focus on the effects of COVID-19 lockdowns in China in Section 3. We explore the heterogeneity of the death of distance in Section 4 and underscore the remote communication technology as a potential contributing factor to the death of distance. We discuss the economic implications of the death of distance in VC investment in Section 5. Section 6 concludes.

2 The death of distance in VC investment

Confronted with the unprecedented and stringent COVID-19 mobility restrictions, how have the VC investors adjusted their investment decisions to address such disruptions? We investigate this question based on a sample of global VC investments as described in Section (2.1). We study the decisions of a VC firm to invest in local versus remote startups in Section (2.2). We examine whether such changes in VC-startup distance are different across countries with distinct stringencies of human mobility restrictions in Section (2.3).

2.1 Data

Our primary data source for global VC investments is the Refinitive VentureXpert database. We trace how VC investments evolved in the recent five years (i.e., 2017–2021) and we compare investments made by each VC firm during the post-pandemic period (i.e., 2020–2021) with deals made by the same VC firm in the pre-pandemic period (i.e., 2017–2019).[9] Our analysis is based on VCs having at least one investment in both the post-pandemic period and the pre-pandemic period.[10] We focus on domestic deals (i.e., investments made from VCs to startups in the same country) in our baseline estimations. The sample of domestic VC investments covers 76,527 deals made from 4,086 VC firms to 24,135 startups in 49 countries.[11] These countries account for 90.0% of global GDP and 73.1% of the global population in 2019. We plot the global distribution of domestic VC investments in Appendix Figure IA1 where darker regions indicate a higher level of VC investments. As illustrated by this figure, VC financing has covered most developed countries and major fast-growing developing economies. Following previous studies (e.g., Tian (2011)), we compute the distance between VCs and startup companies in each deal based on the latitude and longitude information of each pair of cities.[12]

We use the Oxford COVID-19 Government Response Tracker (OxCGRT) to examine government restrictions on human mobility during the COVID-19 pandemic. OxCGRT is a comprehensive database tracking COVID-19 mobility restriction policies across a standardized series of indicators in more than 180 countries. Based on such information, the OxCGRT database creates composites indices to gauge the stringency of the government restrictions on human mobility. OxCGRT also reports specific human mobility restriction polices, including government restrictions on canceling public events, bans on social gatherings, restrictions on domestic travels, the closings of public transport, the closings of workplaces, and the government mandate on the "shelter-in-place" orders.

We provide summary statistics for the domestic deals (i.e., investments made from VCs to

[9] The year 2017 is incorporated as the omitted group in the regressions.

[10] Our findings are even stronger when this condition is not incorporated (i.e., when including a VC in the sample as long as it has made one investment between 2017 and 2021), though more detailed results are not reported due to space limit.

[11] While we focus on domestic deals in our baseline estimations, we also report the results when cross-border deals are included in Appendix Table IA5 and our findings are robust.

[12] We applied the Vincenty's formula to calculate the distance between each pair of cities. Vincenty's formula is the leading approach in geodesy to calculate the distance between two points on the surface of a reference ellipsoid.

startups in the same country) in Appendix Table A2. All potentially unbounded variables are winsorized at the 1% extremes unless otherwise specified. The average VC firm in the sample is about 16 years old and invests in startup companies located 1,078 kilometers (670 miles) away. The average startup company in the sample operates in an industry with an R&D-to-asset ratio of 16.6%, a market-to-book ratio of 3.2, and an asset tangibility ratio of 12.9%.[13] On average, the VCs and the startups face a real GDP growth rate of 1.2% and a mobility restriction index of 61.0.

2.2 VC investors during the pandemic: Invest local or remote?

2.2.1 Baseline analysis

Since COVID-19 lockdowns created major obstacles to visiting entrepreneurs in distant regions, do VCs refrain from investing in remote ventures during the pandemic? To investigate this question, we start by characterizing the distribution of the distance between VCs and startup companies around the world in Figure 1. We focus on domestic deals (i.e., investments made from VCs to startups in the same country) in this figure. We compare the VC-startup distance distribution during the two years after the pandemic (i.e., 2020–2021) with its counterpart during the two years before the pandemic (i.e., 2018–2019). As depicted in Figure 1, the VC-startup distance distribution during the post-pandemic period first-order stochastically dominates its pre-pandemic counterpart. Therefore, VCs tend to invest in more distant startup companies after the COVID-19 pandemic.

[Insert Figure 1 Here.]

One may wonder if the changes in Figure 1 are driven by particular country or industry outliers. In light of such concerns, we compare the average distance between VCs and startup companies in each country two years after the pandemic (i.e., 2020–2021) with the average VC-startup distance

[13] The market-to-book ratio refers to the ratio of the sum of the market value of equity and book value of debt to the sum of the book value of debt and equity. The asset tangibility ratio refers to the net value of property, plant, and equipment divided by the book value of assets. These industry-level proxies are based on U.S. listed firms during the decade before the COVID-19 pandemic (i.e., 2010–2019). We compute each ratio for each firm and take the median across firms as the industry-level proxy. Following previous studies (e.g., Gompers (1995), Tian (2011)), these industry-level proxies are used to gauge the degree of information asymmetry between the VCs and the startups and more details can be found in Section 4.3.

during the two years before the pandemic (i.e., 2018–2019) in Figure 2. To visualize the relative importance of each country, the size of the circles in Figure 2 is proportional to the number of deals in each country. Analogously, we plot the average distance between VCs and startup companies in each industry during the post-pandemic period against its pre-pandemic counterpart in Figure 3. The size of the circles in Figure 3 is proportional to the number of deals in each industry. We add a 45-degree line in both figures to facilitate the comparison. Comparing VC-startup distance during the post-pandemic period with its pre-pandemic counterpart in Figure 2 (3), the majority of countries (industries) lie above the 45-degree line. Hence, increasing VC-startup distance after the pandemic does not seem to be driven by particular country or industry outliers.

[Insert Figure 2 Here.]

[Insert Figure 3 Here.]

One may be concerned that the changes after the pandemic are driven by different compositions of VC firms and startup companies. One may also wonder if the changes after the pandemic are merely reflecting a long-run trend that does not necessarily bear any relationship with COVID-19. To address these concerns, we trace how VC-startup distance evolved in the following deal-level regressions:

$$
\begin{aligned}
y_{i,j,c,t} = {} & \beta_1 \times \mathit{COVID1} + \beta_2 \times \mathit{COVID2} + \sum_{\tau} \eta_\tau \times T_\tau + \theta' X_{i,t} + \delta' X_{j,t} + \eta' X_{c,t} \\
& + \mathit{VC}_i + \mathit{Industry}_j + \mathit{Round}_j + \mathit{Quarter}_t + \epsilon_{i,j,t}
\end{aligned} \tag{1}
$$

In this equation, the subscript i indexes for VC firms, j indexes for startup companies, c indexes for countries, and t indexes for quarters. To assess whether the changes in VC investment strategies after the pandemic are merely a reflection of a long-run trend, we compare investments made by a VC firm two years after the pandemic (i.e., 2020–2021) with deals made by the same VC firm during the past three years before the pandemic (i.e., 2017–2019). The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. T_τ represents for a set of year dummies for previous year τ. $X_{i,t}$, $X_{j,t}$ and $X_{c,t}$ are vectors of control variables for the VC firms, the startup companies, and their countries.[14] To be specific, we control for the age of the VC firms, the age of the startup companies, as well as the country-level GDP growth rate and number of patent applications via the Patent Cooperation Treaty (both with a one-year lag).[15] We include VC fixed effects (VC_i) and industry fixed effects ($Industry_j$) to control for all time-invariant heterogeneity at the level of VCs and startup industries. We incorporate funding round fixed effects ($Round_j$) in light of the importance of stage financing documented in previous studies (e.g., Tian (2011)). The quarter fixed effects ($Quarter_t$) is also added to control for seasonality.[16] β_1 and β_2 capture the changes in VC-startup distance after the pandemic, and, thus, are the key regression coefficients of interest. We cluster the standard errors at the country level and report the estimation results in Table 1.

The results in Table 1 suggest that the distance between VCs and startup companies has significantly increased after the pandemic. According to regression (4) of Table 1, a VC firm invests in startup companies that are 11.4% (about 123 kilometers) farther away in 2020, compared to the investments made by the same VC firm in 2017 (the omitted group). Such an increase in VC-startup distance has further expanded to 29.7% (about 320 kilometers) in 2021. In addition, the estimates of the 2018 and 2019 dummies indicate that VC-startup distance has not significantly changed before 2020. In contrast, the regression coefficient becomes statistically significant and the magnitude of the estimates surges after the pandemic: Regression (4) suggests the estimates of *COVID1* and *COVID2* are 5 and 13 times larger than the estimate of the 2019 dummy. Such abrupt and drastic changes after the pandemic are presumably too large to be rationalized by a long-run estimate documented in the literature (e.g., Petersen and Rajan (2002)).[17] In addition,

[14]Since we focus on domestic deals (i.e., investments made from VCs to startups in the same country) in this section, the VCs and startups are always in the same country.

[15]Following previous studies (e.g., Bernstein et al. (2016)), the number of years since a startup's first round of financing is used as the proxy of the startup age.

[16]While we incorporate quarter fixed effects in our baseline estimations, we also report the results based on month fixed effects and day fixed effects in Appendix Table IA1 and our findings are robust.

[17]Petersen and Rajan (2002) find that the growing use of information technology has led to increasing distance between small firms and their financiers in the United States. Nonetheless, subsequent studies indicate that the U.S. experience of increasing lender-borrower distance is not necessarily manifested in other countries. For instance, Degryse and Ongena (2005) show that lender-borrower distance in Belgium has not increased over time. In this context of global VC investments, the positive regression coefficients of the 2018 and 2019 dummies in Table 1 are to some extent in line with Petersen and Rajan (2002)'s findings that the VC-startup distance might be trending

we demonstrate in Table 4 in the next section that such an increase in VC-startup distance is not manifested among deals made in 2020 but *before* the lockdown restrictions were imposed. In light of this, the changes in VC investment strategies after the pandemic are unlikely to be mere reflections of a long-run trend. Instead, the death of distance in VC investment has presumably revealed the effects of the COVID-19 pandemic and lockdowns. While the post-pandemic period has not been long enough to reach any solid conclusions, the persistence and acceleration of the death of distance in 2021 constitute early suggestive evidence that the changes in VC investment strategies during the Great Lockdown may herald long-lasting transformations in the post-pandemic era.

[Insert Table 1 Here.]

2.2.2 Robustness checks

Built on our baseline estimation results, we conduct five robustness checks in this section to assess the sensitivity of our findings on the death of distance in VC investment.

Relocation of the entrepreneurs. Some entrepreneurs may relocate after the COVID-19 pandemic and some VCs may chase such entrepreneurs. Hence, one may wonder if increasing VC-startup distance can be driven by the relocation of the entrepreneurs after the pandemic. To mitigate this concern, we report the results based on startup companies founded before the pandemic in Appendix Table IA2.[18] As demonstrated by the results in this table, the pattern of increasing VC-startup distance after the pandemic is robust.[19]

up. However, the regression coefficients of the 2018 and 2019 dummies are not statistically significant and their magnitudes are much smaller than the estimates of the COVID-19 indicators. Hence, the significant changes in VC investment strategies after the pandemic are unlikely to be mere reflections of a long-run trend, but have presumably revealed the effects of the pandemic and lockdowns, instead. As a comparison, Petersen and Rajan (2002) provide a long-run estimate that the distance between small firms and their financiers is growing at 3.4% per year, whereas Table 1 suggests the distance between VCs and startup companies has increased by 11.4% in 2020 and 29.7% in 2021. Thus, such abrupt and drastic changes after the pandemic are presumably too large to be rationalized by a long-run estimate. Note that Petersen and Rajan (2002) attribute the increase in lender-borrower distance to the growing use of information technology. Viewed from this perspective, to the extent that there exists a secular increase in VC-startup distance in global VC investments, the COVID-19 pandemic and lockdowns may have substantially accelerated such "death of distance" by spurring the advancement and adoption of information technology that addresses the social distancing requirements. We will elaborate on this issue in Section 4.

[18] Following previous studies (e.g., Bernstein et al. (2016)), the number of years since a startup's first round of financing is used as the proxy of the startup age. Since these startup companies received their first round of financing before the COVID-19 pandemic, they must have been founded before the pandemic. In addition, we also ensure that the deals occurred in the cities of the startup headquarters in this test.

[19] Even in the absence of relocation of the entrepreneurs, one may still wonder if increasing VC-startup distance may

Syndicated deals. Some VC investments are syndicated and the lead investor in a syndicated deal typically has stronger incentives to gather information about the startup companies and monitor the ventures (e.g., Gompers et al. (2016)). Thus, one may wonder if the VC-startup distance has increased because some investors in syndicated deals could free ride on the lead investors. To alleviate this concern, we focus on deals made by the lead VC investors in Appendix Table IA3 and our findings are robust.

First-round investments. One may also be concerned that some information about the startup companies may have already been disclosed to the VC community in their previous financing rounds. To address this concern, we examine the first-round investments received by the startups in Appendix Table IA4 and the pattern of increasing VC-startup distance after the pandemic is still manifested.

Cross-border deals. Since we focus on domestic deals (i.e., investments made from VCs to startups in the same country) in our baseline estimations, one may wonder if the results will change when cross-border deals are incorporated. Hence, we also include cross-border deals in the regressions in Appendix Table IA5 and our findings are robust.[20] As will be shown in our subsequent analysis in Section (5.2), VCs are also more likely to invest in foreign startups after the pandemic.

Pecking order by geographic proximity. If the VCs are financially constrained, one may wonder if they may follow a pecking order investment pattern by geographic proximity (i.e., proceeding from local startups to remote ventures). Under this pecking order hypothesis, VCs may invest in more distant startups after the COVID-19 pandemic if they have made more investments after the pandemic. We test this pecking order hypothesis in Appendix Table IA6 and IA7.

We examine how the number of investments made by the VCs evolved in VC-year-level regressions in Appendix Table IA6. We report the results without VC fixed effects in regression

be driven by diversification concerns of the VCs in the aftermath of the COVID-19 pandemic. While diversification is a major concern for some types of financial institutions (e.g., commercial banks), it does not constitute a first-order-important motive for VC investors. Despite being confronted with huge idiosyncratic risks and failures in many portfolio companies (e.g., Hall and Woodward (2010)), the VCs primarily focus on searching for a small number of home run investments to earn an impressive average return.

[20]The VCs and the startups may be located in different countries when cross-border deals are included, and the standard errors are clustered by the countries of the VCs in such regressions.

(1) of Table IA6 and we incorporate the VC fixed effects in regression (2). In both regressions, the number of investments made by the VCs has not significantly changed in 2020, whereas the VC-startup distance has significantly increased in 2020. Such changes in 2020 do not support the pecking order hypothesis. After including VC fixed effects in regression (2), the number of VC investments has not significantly changed until 2021. To further test the pecking order hypothesis, we delve into the deal-level regressions in Appendix Table IA7. To the extent that the death of distance is driven by the pecking order hypothesis, we expect to observe a more salient increase in VC-startup distance when the number of VC investments experienced a larger rise after the pandemic. In light of this, we interact the COVID indicators with the post-pandemic changes in the number of VC investments in deal-level regressions in Appendix Table IA7. In regression (1) of Table IA7, we interact the COVID indicators with the change in the number of investments relative to 2019 (i.e., one year before the pandemic) of each VC firm. The interaction term in regression (2) is the percentage change in the number of VC investments relative to 2019. We also interact the COVID indicators with the level of the number of investments made by each VC firm in regression (3). Since none of the interaction terms in Table IA7 is statistically significant, the symptom of increasing VC-startup distance does not seem to be linked to any potential changes in the number of VC investments after the pandemic. In light of this, the pecking order hypothesis does not seem to be a first-order-important explanation for the death of distance in VC investment after the pandemic.[21]

2.3 COVID-19 restrictions on human mobility

Many countries have adopted various restriction policies on human mobility to contain the spread of the COVID-19 pandemic. We assess the role of government restrictions on human mobility in Table 2. The empirical setup of the regressions in Table 2 is the same as that in Table 1, except that we interact the COVID indicators with the OxCGRT measure of the stringency of mobility

[21] One may also wonder if on-site visits may become infeasible for all ventures when VCs are confronted with uttermost lockdown restrictions. In such extreme scenarios, one may wonder if VCs are equally likely to invest in local and remote ventures when facing a lockdown, controlling for the quality of startup companies. Though such an extreme-case-based argument may be instrumental to explain the changes in VC investment strategies when VCs face utmost lockdown restrictions, it is unable to explain why the death of distance has persisted and even accelerated in 2021 when such uttermost lockdown restrictions have been lifted or relaxed in most countries.

restrictions. *Restriction stringency* in Table 2 is the natural logarithm of this measure of mobility restriction stringency in each country.[22] The results in Table 2 indicate that the death of distance in VC investment is more pronounced in countries with more stringent human mobility restrictions. Consider a comparison between the United States and China, two nations with a salient difference in their approaches to combat the COVID-19 pandemic. Compared to the situation in 2017 (the omitted group), regression (4) of Table 2 suggests that VC-startup distance in 2020 has ratcheted up by 9.4% (about 101 kilometers) in the United States and 21.5% (about 232 kilometers) in China. In 2021, VC-startup distance has risen by 11.3% (about 122 kilometers) in the United States and 24.7% (about 266 kilometers) in China.

[Insert Table 2 Here.]

We delve further into the specific human mobility restriction policies in Table 3. *Cancel public events* is a proxy of the stringency of government restrictions on canceling public events in each country. *Restrictions on gatherings* is a proxy of the stringency of government bans on social gatherings. *Travel restrictions* is a proxy of the stringency of government restrictions on traveling. *Public transport closings* is a proxy of the stringency of government mandate on the closings of public transport. *Workplace closings* is a proxy of the stringency of government mandate on the closings of workplaces. *Stay at home* is a proxy of the stringency of government mandate on the "shelter-in-place" orders.[23] According to the results in Table 3, the death of distance in VC investment is more pronounced in countries where these mobility restriction policies are more stringent. This is suggestive evidence that the death of distance in VC investment after the COVID-19 pandemic could be related to government restrictions on human mobility. Built on such evidence from the global VC investments, we will sharpen our analysis of the role of mobility restrictions by focusing on COVID-19 lockdowns in China in the next section.

[Insert Table 3 Here.]

[22] Since this restriction stringency measure is time-varying, the separate term of this measure is also included in the regressions (though not reported in this table for brevity).

[23] All these measures of the stringency of mobility restriction policies are based on the subindices of the OxCGRT mobility restriction measure and they are included in the regressions in natural logarithms. Since these restriction stringency measures are time-varying, the separate term of these measures is also included in the regressions (though not reported in this table for brevity).

3 COVID-19 lockdowns and VC investment in China

One may be concerned about country-level unobservables for our findings based on our global study in the previous section. Parallel to our study based on global VC investments, we alleviate the concern for country-level unobservables by probing the effects of COVID-19 lockdowns in one country–China. We focus on China because it is the first country to be severely hit by the COVID-19 pandemic. China is also the first country to impose drastic restrictions (such as lockdowns and face mask mandates) to contain the spread of COVID-19 and its restrictions are among the most stringent in the world. To the extent that China's experience constitutes a precedent for other countries that were subsequently stricken by COVID-19, the COVID-19 pandemic is more eligible to be an *unanticipated* shock in the Chinese context. In light of this, China provides an ideal setting to investigate the effects of COVID-19 lockdowns.

China has become the second-largest country in the world in terms of VC investments (Huang and Tian (2020)) and a dazzling array of world-class technology companies (such as Alibaba and Tencent) has been incubated by China's VC industry. In our study of the VC industry in China, we augment VentureXpert with the CVSource database, a comprehensive data set on venture capital and private equity investments in China.[24] We outline the institutional background of COVID-19 lockdowns in China in Section (3.1). Exploiting the regional differences in lockdowns and reopening in China, we examine the effects of lockdowns based on the government lockdown mandate in Section (3.2). We study the effects of lockdowns based on the human mobility level in Section (3.3), and we distinguish between different phases of lockdowns and reopening to sharpen our analysis.

3.1 COVID-19 and lockdowns in China

The outbreak of the COVID-19 pandemic in China was first reported from Wuhan in late 2019. The World Health Organization issued its first report on the COVID-19 outbreak on January 5, 2020. Appendix Figure IA2a and IA2b track the number of new COVID-19 cases and the number

[24] The name of VCs and startups are recorded in Chinese in CVSource and it facilitates merging the VC data with other databases. For instance, we obtain the patenting information of the startup companies by merging CVSource with the patent database of the Chinese National Intellectual Property Administration (CNIPA).

of deaths from COVID-19 in China over time. To highlight the peak of the COVID-19 pandemic in China, we zoom in on the first quarter of 2020 in Appendix Figure IA2c and IA2d. Starting around early February, the number of COVID-19 cases and deaths surged as the pandemic spread from Wuhan to all regions of China.

To contain the spread of the COVID-19 pandemic, the Chinese government started to impose lockdown mandates to restrict human mobility across regions.[25] In accordance with the *Emergency Response Law of the People's Republic of China*, level-I government emergency response was gradually triggered across regions, as COVID-19 spread around the country. Under level-I government emergency response, the State Council of China centralized the decision-making power on major public policies to combat the pandemic and coordinated the measures taken by various levels of local governments. As a consequence, all cities in China must defer to the command of the State Council under level-I government emergency response. After the number of new COVID-19 cases in China started to decline, the government emergency response level was gradually reduced to level II across regions. Under level-II government emergency response, the central government delegated the decision-making power to combat the pandemic to the provincial governments. Within a province, all cities must comply with the policies formulated by their provincial government under level-II government emergency response. As the pandemic was largely brought under control, level-II government emergency response was gradually phased out across regions. After the termination of level-II government emergency response, the decision-making power was finally returned to each city and most severe travel restrictions have ultimately been lifted. In light of this, when examining the effects of lockdowns based on government mandate in our baseline estimations, a province is classified to be under lockdown when level-I or level-II government emergency response is effective. Reopening refers to the period when the lockdown restrictions have been lifted (i.e., when level-II government emergency response has been phased out).

The lockdown and reopening periods in each province of China are visualized in Figure 4. The horizontal axis of Figure 4 is the timeline. The solid lines and dashed lines represent the lockdown and reopening period, respectively. There was remarkable regional variation in the length of the

[25] For instance, all inter-province passenger transportation was banned in Beijing.

lockdown period and the timing of reopening. Some provinces (e.g., Fujian) started to reopen as early as February, whereas some provinces (e.g., Hebei) did not reopen until June. While the lockdown period was less than one month for two provinces (27 days for Gansu and 28 days for Liaoning), it was longer than 100 days for nine provinces (about 29% of the provinces in China). Hubei (the province hit the hardest by COVID-19) was confronted with a lockdown of 143 days and the longest lockdown (168 days) occurred in Beijing.

[Insert Figure 4 Here.]

As demonstrated in Fang et al. (2020), COVID-19 lockdowns in China have led to an abrupt and substantial decline in the level of human mobility. We track the monthly passenger flows in China in 2020 and the past three years (i.e., 2017–2019) in Appendix Figure IA3.[26] In the aftermath of the COVID-19 lockdown, passenger flows in China plummeted by 85.4% between January and February 2020. As the lockdown restrictions phased out, passenger flows in China started to gradually recover during the reopening stage. In light of this, we adopt two lockdown proxies (one based on the government lockdown mandate and another one based on the actual human mobility level) in our subsequent analysis.

3.2 Lockdown effects based on government mandate

As delineated in the previous section, China initially reacted to the outbreak of COVID-19 with strict lockdown restrictions, whereas the severe mobility restrictions have been largely lifted as the pandemic was brought under control during the second half of 2020. In light of this, we focus on comparing VC investments made in 2020 with deals in 2019 to sharpen our analysis of the lockdown effects. In the following deal-level regressions, we conduct this comparison among deals made before

[26] The statistics on passenger flows account for all transportation methods and are expressed in terms of the number of trips. The data on passenger flows are sourced from China Railway Corporation, the Ministry of Transport, Civil Aviation Administration, China Petroleum and Natural Gas Corporation Group, China Petrochemical Corporation Group, and the divisions of vehicle management. We obtain the passenger flows data from the CEIC database.

the lockdown, during the lockdown, and after the reopening:

$$y_{i,j,t} = \alpha + \beta_1 \times COVID \times Before_{i,j,t-\tau} + \beta_2 \times COVID \times Lockdown_{i,j,t-\tau}$$
$$+ \beta_3 \times COVID \times Reopen_{i,j,t-\tau} + \phi_1 Before_{i,j,t-\tau} + \phi_2 Lockdown_{i,j,t-\tau} + \phi_3 Reopen_{i,j,t-\tau}$$
$$+ \theta' X_{i,t-\tau} + \delta' X_{j,t-\tau} + VC_i + Industry_j + Round_j + Day_t + \epsilon_{i,j,t} \tag{2}$$

Equation (2) builds on Fang et al. (2020)'s empirical setup to study the lockdown effects in China. In addition, we extend Fang et al. (2020)'s setting to cover the reopening phase as well. The subscript i in equation (2) indexes for VC firms, j indexes for startup companies, and t indexes for days. The dependent variable $y_{i,j,t}$ is the natural logarithm of one plus the distance between VC firm i and startup company j. In light of the time needed for due diligence and deal-making as reported in Gompers et al. (2020), all independent variables are lagged by ten weeks (i.e., the time lag τ in equation (2) equals seventy days) in our baseline estimations.[27] The regression sample covers all VC investments made in 2020 and 2019. The *COVID* dummy takes the value of one for VC investments made in 2020 and equals zero for deals made in 2019. The *Lockdown* dummy equals one if either the VC firm or the startup company is facing a lockdown and zero otherwise. The *Reopen* dummy is equal to one if the lockdown is lifted for both the VC firm and the startup company and zero otherwise. To assess the parallel trend assumption, the *Before* dummy takes the value of one for the period of four weeks before the lockdown restriction is imposed and zero otherwise. The omitted period is from January 1, 2020, to the date when the *Before* dummy switches to the value of one.[28] We incorporate VC fixed effects (VC_i), industry fixed effects ($Industry_j$), and funding round fixed effects ($Round_j$) to control for all time-invariant heterogeneity at the level of VCs, startup industries, and funding rounds. Following Fang et al. (2020), we include day fixed effects (Day_t) to absorb the aggregate shocks, including a series of important events during this sample

[27]Since Gompers et al. (2020) report that it takes about ten weeks for VCs to close a deal, the time lag is taken to be seventy days in our baseline estimations. The findings are robust when using a shorter or longer time lag (e.g., Table IA8 reports the results with a time lag of fifty days).

[28]For instance, the lockdown restrictions in Shanghai were introduced on January 24 and lifted on May 8, 2020. With a ten-week period for due diligence and deal-making, deals accomplished between April 3 and July 17 were associated with the lockdown status. Deals sealed between July 18 and December 31 were associated with the reopening status. Deals made between March 6 and April 2 were associated with the "before" status and deals between January 1 and March 5 constitute the omitted group.

period that could be associated with significant effects at the daily frequency.[29] We control for the age of a startup company and the number of its patents at the time of the investment. Patenting information of the startup companies is obtained from the Chinese National Intellectual Property Administration (CNIPA). Table 4 reports the estimation results.

[Insert Table 4 Here.]

Since the regression coefficient of $COVID \times Before$ in Table 4 is statistically insignificant (and the estimate actually features a negative sign), no pre-existing trends are manifested in the data. Since the changes of VC investment strategies in 2020 were not observed *before* the lockdown restrictions were imposed, such changes are unlikely to be mere reflections of a long-run trend, echoing our findings in the previous section. In contrast, the significant and large estimates of $COVID \times Lockdown$ and $COVID \times Reopen$ in Table 4 indicate that the changes of VC investment strategies in the pandemic year have presumably reflected the effects of the COVID-19 lockdowns. According to the positive estimate of $COVID \times Lockdown$ in Table 4, a VC firm invests in more distant startup companies when facing a lockdown in 2020, compared to the investments made by the same VC firm during the same period in the previous year. The positive estimate of $COVID \times Reopen$ suggests that such effects persist even after the lockdown is lifted. According to regression (3) of Table 4, a VC firm invests in startup companies that are 22.3% farther away during a lockdown and 18.5% farther away after the reopening. Contrary to the conventional wisdom that lockdowns exacerbate the tyranny of distance (and echoing our results based on global VC investments), our findings suggest the death of distance in VC investment in China: VCs invest in more distant ventures during a lockdown and such effects are enduring after the economy reopens.

3.3 Lockdown proxies based on human mobility level

COVID-19 lockdown restrictions in China are stringent and the government mandate has been strictly enforced. As a consequence, it is well-documented (e.g., Fang et al. (2020)) that government

[29] For example, China's Spring Festival during this sample period is associated with the largest human migration in the world. In addition, there was a major panic when public health experts officially confirmed that the COVID-19 virus could be transmitted through person-to-person contact. As demonstrated in Fang et al. (2020), such events were associated with a large impact (particularly significant changes in the human mobility level) at the daily frequency and, thus, we incorporate day fixed effects to absorb such aggregate shocks.

lockdown restrictions in China have led to substantial reductions in the level of human mobility. Nonetheless, one may still wonder how the effects change if the lockdown is defined with respect to the actual human mobility level instead of the government lockdown mandate. One may also wonder if the stringency of lockdown restrictions could vary across different provinces and vary across different cities within the same province. In addition, voluntary social distancing can contribute to reducing the human mobility level in the absence of any government restrictions. Moreover, the reopening of the economy and the recovery of economic activities is a gradual process and one may wonder how the effects evolve across different phases of reopening and recovery. To address these concerns, we study the effects of lockdowns defined by the human mobility levels in this section.

Our definition of human-mobility-based lockdowns builds on Ozik et al. (2021). While Ozik et al. (2021) is based on a nationwide lockdown period that features no regional differences, we sharpen our analysis by exploiting the regional differences in lockdowns and reopening in China and pinpointing the lockdown and reopening periods at the city level. To detect the end of the human-mobility-based lockdown period, we define the "trough mobility date" in a city as the date when this city hit its lowest level of human mobility in 2020. The city-level daily human mobility information is gathered from the traffic database of AutoNavi (Gaode), a leading digital mapping platform in China with more than 530 million monthly active users.[30] We obtain the trough mobility date for each city to examine the effects of human-mobility-based lockdowns and we report the results in Table 5.[31]

[Insert Table 5 Here.]

The empirical setup of the regressions in Table 5 is the same as that in Table 4, except that *Lockdown* and *Reopen* in Table 5 are based on the human mobility level. While the end of the lockdown period in our previous analysis corresponds to the termination of the government lockdown

[30] AutoNavi (acquired by Alibaba Group in 2014) is a prominent provider of digital map content, navigation, and location-based solutions in China. Resembling Google map in the United States, AutoNavi (Gaode) map in China is a leading digital mapping platform with more than 530 million monthly active users in 2020. Analogous to Apple's mobility trends index, the AutoNavi (Gaode) human mobility index is based on the requests for directions made by the users of the AutoNavi (Gaode) map.

[31] Since the human mobility information in the AutoNavi traffic database is missing for some cities, the number of observations of the regressions in Table 5 and Appendix Table IA9 is smaller than that in Table 4.

mandate, it is based on the trough mobility date in a city in Table 5.[32] Analogously, the reopening phase in Table 5 refers to the period between the trough mobility date and the end of the year.[33] As demonstrated by the results in Table 5, VCs invest in more distant ventures during a lockdown and such effects persist after the economy reopens. Therefore, our findings on the death of distance in VC investment are robust regardless of whether the lockdown period is based on the government lockdown mandate or the human mobility level.

Since the reopening of the economy and the recovery of economic activities is a gradual process, we divide the reopening process into two phases (i.e., early-stage vs late-stage reopening) in Appendix Table IA9. To be specific, we define the "half-recovery date" to be the date when the human mobility level in a city in 2020 has restored at least one-half of its previous level in 2019.[34] The "early-stage reopening" phase in Table IA9 refers to the period between the trough mobility date and the half-recovery date. The "late-stage reopening" phase in Table IA9 refers to the period between the half-recovery date and the end of the year.

The results in Table IA9 have strengthened our previous findings and unveiled the subtlety of the transition from the Great Lockdown to the post-lockdown period. The significantly positive estimate of "*COVID* $\times$ *Lockdown*" in Table IA9 reinforce our previous findings on the death of distance in VC investment. Though the estimate of "*COVID* $\times$ *Early Reopen*" is positive, it is statistically insignificant at the ten percent level. This is suggestive evidence that the transition

[32]Compared to the government-mandate-based lockdown period, VCs and startup companies tend to face more stringent lockdown restrictions during the human-mobility-based lockdown period. Since the lockdown restrictions tend to ease before they are completely lifted, the human mobility level starts to recover before the official termination of the government lockdown mandate. Thus, the human-mobility-based lockdown period in Table 5 tends to end earlier, compared to the government-mandate-based lockdown period in Table 4. For instance, the government lockdown mandate in Shanghai was introduced on January 24, 2020, and Shanghai's human mobility index hit its lowest level on February 16, 2020. Hence, the human-mobility-based lockdown period in Shanghai is from January 24–February 16, 2020. As a comparison, the government-mandate-based lockdown period in Shanghai is January 24–May 8, 2020. Since the lockdown restriction before February 16 was more stringent than that after February 16, the lockdown restriction during the human-mobility-based lockdown period in Shanghai was on average more stringent than that during the government-mandate-based lockdown period.

[33]To be more specific, we apply this city-level and human-mobility-based definition of lockdown period to both the VC firms and the startup companies. The *Lockdown* dummy in Table 5 equals one if either the VC firm or the startup company is facing this human-mobility-based lockdown period and zero otherwise. The *Reopen* dummy in Table 5 is equal to one if the human-mobility-based lockdown period has ended for both the VC firm and the startup company and zero otherwise.

[34]For instance, the human mobility level in the city of Tianjin in 2020 started to be above one-half of Tianjin's 2019 level on February 25, 2020. Hence, the half-recovery date for Tianjin is defined to be February 25.

to the post-lockdown period may not be a smooth boulevard.[35] Nevertheless, the estimate of "*COVID* $\times$ *Late Reopen*" in Table IA9 eventually turns to be significantly positive. Hence, during the late stage of reopening and after the lockdown restrictions have been further lifted, VCs have eventually decided to continue their lockdown-induced changes and invest in more distant startups, though such a transition may not be a linear process.

4 Heterogeneity of the death of distance

In light of the importance of geographic proximity and on-site visits documented in the literature, conventional wisdom suggests VCs must refrain from investing in remote ventures during lockdowns because visiting startup companies in remote areas becomes substantially more difficult. As demonstrated by our findings in the previous section, however, it is puzzling that the response of VCs to lockdowns is exactly contrary to what conventional wisdom suggests. Nevertheless, the death of distance in VC investment is reminiscent of Petersen and Rajan (2002)'s findings that the growing use of information technology has led to an increasing distance between small firms and their financiers. Echoing Petersen and Rajan (2002), we elaborate on how the advancement and adoption of remote communication technology can be a potential contributing factor to the death of distance in Section (4.1) and we provide supporting evidence through three channels in Sections (4.2)–(4.4).

4.1 Advancement and adoption of remote communication technology

Bloom et al. (2021) document that the COVID-19 pandemic has re-directed innovations toward technologies in support of video conferencing, telecommuting, remote interactivity, and working

[35] During the early stage when the lockdown restrictions start to be removed, VC investors need to digest the lockdown lessons learned from their experimentations to address the COVID-19 disruptions, and reflect on whether to continue the lockdown-induced changes in their investment strategies in the post-lockdown period. As will be elaborated in the next section, a major lockdown-induced change in VC investment strategies is the increasing reliance on remote communication technology (e.g., Zoom) to bypass the lockdown restrictions and gather information about the entrepreneurs. Viewed from this perspective, the positive but insignificant estimate of "*COVID* $\times$ *Early Reopen*" may be suggestive evidence for such reflections of the VC investors during the transition and their post-lockdown readjustment process during the early-stage reopening.

from home. The advancement and adoption of digital technologies (e.g., the 5G technology,[36] artificial intelligence,[37] big data,[38] cloud computing,[39] robotics,[40] and the internet of things[41]) has been of vital importance in combating COVID-19 and maintaining business operations despite the disruptions of the pandemic.

In particular, a myriad of technological innovations for remote communication has been swiftly created and widely adopted to address the pandemic-induced social distancing requirements. For instance, Zoom featured 300 million daily meeting participants in 2020 and held more than 3.3 trillion meeting minutes on an annual basis. As a response to the enhanced quality and productivity of remote communication, many VCs have seized this technological opportunity and transformed some of their traditional in-person activities into online meetings. For instance, Sequoia Capital China introduced its first "Online Demo Day" on February 18, 2020. This Online Demo Day was an invite-only pitch event connecting 33 promising startups with 50 actively investing VC firms. This event was widely applauded by both the startups and the investors. According to the survey of Sequoia Capital China, 100% of startups were satisfied with the way the event was organized (one startup received an offer within one hour after the event). The investors had a rating between 4.62 and 4.65 (out of 5.00) for the event organization and a rating between 7.93 and 8.00 (out of 10.00) for the quality of startups. Echoing the initiative of Sequoia Capital China, the business practice of moving some VC activities online is manifested in many countries around the world.[42]

[36]For instance, the 5G technology has been applied to safeguard emergency communications, empower medical response to the pandemic, develop COVID-19 telemedicine collaboration solution, promote remote education, enhance city containment and disease control, predict urban epidemic tendency to facilitate epidemic prevention, and support the resumption of work and production during the economic recovery. Elaborate studies of each 5G technology application can be found in the report of the Global System for Mobile Communications Association (GSMA), "Mobile Industry Response to COVID-19 in China," April 2020.

[37]For instance, Baidu Research (an artificial intelligence research wing of Baidu) developed an artificial intelligence algorithm for gene testing, reducing the time taken to predict and study coronavirus's RNA secondary structure from 55 minutes to just 27 seconds.

[38]For instance, Qihoo 360 (an internet company in China) released its "Big Data Migration Map" to aid the prediction of migration trends and epidemic situations.

[39]For instance, Alibaba Cloud (a cloud computing services provider) made its GPU cloud computing resources to public research institutions for free to accelerate the development of new pneumonia drugs and vaccines.

[40]For instance, Meituan (a Chinese online shopping platform for locally found consumer products) deployed autonomous contactless delivery robots for quarantined households to order and receive essential household items.

[41]For instance, Ghaleb et al. (2021) document how various types of internet-of-things-based technological solutions have contributed to defeating the COVID-19 pandemic.

[42]For instance, START Demo Day in Europe was held in a fully virtual format in August 2020. This event has become Europe's largest Demo Day, attracting over 500 startups and 250 investors with combined assets under management of €100 billion. In the United States, the Founder Institute has organized over 80 demo days and startup

Thanks to enhanced remote communication technology and bolstered digital capabilities of the VCs, the costs of communicating with remote entrepreneurs and monitoring their businesses have remarkably declined, incentivizing the VCs to invest in more distant ventures. Echoing our findings on the death of distance in VC investment, there has been a wealth of evidence demonstrating that digital technologies are crucial to addressing the COVID-19 challenges and the shift of some business activities toward remote communication can persist in the post-pandemic era in the United States,[43] in China,[44] in Europe,[45] and all around the world.[46] In light of the sheer importance of the costs of communicating with the entrepreneurs and monitoring the ventures in the VC industry,

webinars by the end of 2021. The Syndicate and Y Combinator have also moved their demo day events online.

[43]Barrero et al. (2021) report that U.S. workers supplied half of the paid workhours from home between April and December 2020 and project that 20 percent of full workdays will be attributed to work from home *after* the COVID-19 pandemic. Barrero et al. (2021) shows the persistent shift toward remote work is driven by better-than-expected experiences in working from home during the pandemic, investments in physical and human capital on telecommuting, the waning stigma associated with distance working, lingering concerns about crowds and contagion risks, and a pandemic-driven surge in technological innovations supporting remote work. According to the COVID-19 report released by the Pew Research Center, the internet has become essential or important for 90% of Americans during the pandemic. This number is as high as 96% for Americans with a college degree. 81% of Americans have used video calling and conferencing during the pandemic. 46% of Americans working from home have used video calling daily or several times a day during the pandemic. Among Americans who have used digital technologies in new or different ways, 43% attributed the changes to video calling. See more details in the Pew Research Center report on "The Internet and the Pandemic," September 1, 2021.

[44]Huang et al. (2021) provide empirical evidence that digital technologies have contributed to addressing the COVID-19 challenges in China by moving many economic activities online and such digital transformations can have long-lasting effects in the post-pandemic era. According to Butt (2022), companies in China implemented agile information technology systems and shifted business activities online to mitigate the COVID-19 disruptions and maintain business operations. It is well-documented that digital health technologies have been of crucial importance to meet the COVID-19 challenges in China. For instance, Cai and Cai (2020) document that virtual-reality technology (backed by the 5G mobile network) has reduced direct in-person contact for the medical staff by enabling remote diagnosis and treatment monitoring of patients. Boeing and Wang (2021) show that community-based digital contact tracing technology contributes to curbing the transmission of COVID-19 in China.

[45]Lamorgese et al. (2021) document that many Italian firms shifted to remote work both during and after the COVID-19 lockdowns in Italy. In addition, better managed Italian firms were more likely to shift to remote work and it has contributed to enhancing firm performance. According to KPMG's COVID-19 report, the majority of financial institutions in Luxembourg did not allow any of their employees to work from home before the COVID-19 pandemic. As a stark contrast, 82% of financial institutions in Luxembourg report that their employees work from home during the lockdown, 63% of them rely on video conferencing tools to communicate with their clients, 67% of them indicate that adopting digital technologies constitutes a major positive impact of the pandemic, and 72% of them intend to promote remote working in the post-pandemic era. See more details in the KPMG report on "Impacts of the COVID-19 crisis on financial institutions in Luxembourg," July 2020.

[46]Fath et al. (2022) show that businesses in New Zealand adopted digital technologies and strengthened their digital capabilities during COVID-19 to break the barriers of physical distance. As reported in Fath et al. (2022), "before COVID-19, establishing a new relationship with an international business partner required multiple face-to-face meetings, and social gatherings, before signing a deal. Particularly in the Asian context, New Zealand managers viewed personal travel as critical before COVID-19, which required a sizable investment on behalf of the New Zealand business due to the distance to markets." In the aftermath of the COVID-19 pandemic, however, "both New Zealand managers and their international business partners embraced digital technology" and "technology use and acceptance was the most significant change due to COVID."

the advancement and adoption of remote communication technology have reduced such costs and emerge as a potential contributing factor to the death of distance in VC investment. As further supporting evidence, we exploit the heterogeneity of VCs and startups along three dimensions: (i) internet infrastructure, (ii) information asymmetry between VCs and entrepreneurs, and (iii) deal size. To the extent that the death of distance is due to enhanced remote communication technology, we expect stronger effects when there is better internet infrastructure, when the level of information asymmetry between VCs and entrepreneurs is lower, and when the deal size is smaller. We provide supporting evidence for these tests in Section (4.2)–(4.4) as follows.

4.2 Internet infrastructure

As the demand for internet connections soared in the aftermath of the COVID-19 lockdown and the social distancing requirements, the internet infrastructure has been of paramount importance for business operations. It is reported that the internet is essential or important for 90% of Americans during the pandemic.[47] In particular, the effectiveness of remote communication technology hinges on the quality and reliability of the internet. Though online conferencing tools such as Zoom are widely available, their effectiveness for communication is limited for users struggling with poor internet connections, a headache for many individuals and businesses. Even among U.S. broadband users with access to high-speed internet, about one-half of them have experienced problems with the speed, reliability, or quality of their internet connections.[48] It is reported that over 80% of businesses experienced internet connectivity problems and senior executives wasted two hours and fifty minutes every week because of the delay in meetings.[49] Since time is a scarce and valuable resource for both VCs and entrepreneurs, the effectiveness of remote communication will be eroded by low-quality internet infrastructure.

Based on the city-level data of internet latency (a notorious culprit for "Zoom lags"), we assess the role of the internet infrastructure in Table 6. We gathered the information on internet latency

[47] See more details in the Pew Research Center report on "The Internet and the Pandemic," September 1, 2021.

[48] More details can be found in the Pew Research Center report on "The Internet and the Pandemic," September 1, 2021.

[49] See more details about the internet connectivity problems in the Radius Global Market Research and WiredScore report on "Businesses Experiencing Internet Connectivity Problems," October 31, 2017. See more details about the time wasted because of the delay of meetings in the Omdia report "Collaboration 2.0," March 5, 2017.

of each city from Ookla's Speedtest Global Index Database.[50] *Internet latency* in Table 6 is the greater value of the internet latency faced by the VC and the startup in each deal.[51] The results in Table 6 suggest that the death of distance in VC investment is less pronounced when there is higher internet latency. Compared to the situation in 2017 (the omitted group), regression (4) of Table 6 suggests that VC-startup distance has ratcheted up by 53.8% (about 580 kilometers) for the average VC in San Francisco in 2021, whereas this number is only 27.3% (about 294 kilometers) for the average VC in Mexico City. The heterogeneity of the death of distance with respect to internet speed has uncovered both the contributions and the limitations of remote communication: While high-quality internet infrastructure enables remote communication and incentivizes VCs to invest in remote startups, low-quality internet infrastructure fails to provide such incentives to VCs, and on-site visits and in-person meetings remain essential for VCs to gather information about the startups.

[Insert Table 6 Here.]

4.3 Information asymmetry

The VC investment process is intrinsically embedded with information asymmetry problems because certain information about the ventures is possessed by the entrepreneurs, but not the VCs. Despite the enhanced effectiveness of remote communication technology in the aftermath of the COVID-19 pandemic, online conferences could still be insufficient to obtain specific information about the ventures, especially when such information is "soft" (Stein (2002)). To the extent that on-site visits and in-person meetings could be more successful in acquiring such soft information and resolving the asymmetric information frictions, remote communication could be less effective among deals featuring a higher level of information asymmetry, and, thus, we expect to observe weaker symptoms of the death of distance among such deals. In light of this, we evaluate the role of information asymmetry in Table 7. Following previous studies (e.g., Gompers (1995), Tian (2011)), we apply

[50] Ookla is a leading provider of broadband network intelligence and testing applications. Speedtest is Ookla's flagship platform for evaluating internet performance on a global basis.

[51] Since the internet latency information is missing for some cities, the number of observations in this table is smaller than that in Table 1. Since the VCs and the startups may not be in the same city, the separate term of internet latency is also included in these regressions (though not reported in this table for brevity).

the industry-level R&D intensity, market-to-book ratio, and asset tangibility ratio to gauge the degree of information asymmetry between the VCs and the startups.[52] We interact the COVID indicators with these proxies of information asymmetry in Table 7.[53]

According to the results in Table 7, the death of distance in VC investment is less salient when a deal features a higher level of information asymmetry between the VCs and the startups. To illustrate, consider a comparison between the industry "data processing, hosting, and related services" (NAICS: 5182) and "oil and gas extraction" (NAICS: 2111). Compared to the former, the latter features lower R&D intensity, lower market-to-book ratio, and higher asset tangibility ratio. Compared to the situation in 2017 (the omitted group), the last column of Table 7 suggests that VC-startup distance has risen by 51.6% (about 556 kilometers) for the average startup in the industry of data processing, hosting, and related services in 2021, whereas this number is only 27.4% (about 295 kilometers) for the average startup in the industry of oil and gas extraction. The heterogeneity of the death of distance with respect to information asymmetry has unveiled both the effectiveness of remote communication and its limitations. When startup companies operate in sectors with a low level of information asymmetry, remote communication seems to be enough to obtain the information needed for making VC investment decisions, and it may constitute a valid substitute for in-person meetings. However, virtual meetings could be insufficient to gather critical soft information when startup companies operate in sectors with acute information asymmetry frictions, and, thus, on-site visits and in-person meetings may be still essential when VCs are confronted with such severe information asymmetry problems.

[Insert Table 7 Here.]

[52]R&D intensity refers to the R&D-to-assets ratio. The market-to-book ratio refers to the ratio of the sum of the market value of equity and book value of debt to the sum of the book value of debt and equity. The asset tangibility ratio refers to the net value of property, plant, and equipment divided by the book value of assets. These industry-level and time-invariant proxies are based on U.S. listed firms during the decade before the COVID-19 pandemic (i.e., 2010–2019). We compute each ratio for each firm and take the median across firms as the industry-level proxy. The industry classification is based on four-digit North American Industry Classification System (NAICS) codes.

[53]Since the industry information is missing for some startup companies, the number of observations in this table is smaller than that in Table 1.

4.4 Deal size

Deal size could also affect the VC decisions to rely on in-person meetings or remote communication. While a brief virtual meeting may be well enough for "spray-and-pray" deals with a tiny amount of VC investments, in-person meetings could still be essential for crucial deals with hefty financial commitment from the VCs. In light of this, we assess the role of deal size in Table 8.

We interact the COVID indicators with the amount of VC investments (in natural logarithm) in each deal in regression (1) of Table 8.[54] We also report the results based on the real value of VC investments in regression (2). The results in this table indicate that the death of distance in VC investment is less pronounced when the deal size is larger. Compared to the situation in 2017 (the omitted group), regression (1) of Table 8 suggests that VC-startup distance has ratcheted up by 40.5% (about 437 kilometers) in 2021 for the average deal (at the sample mean of the deal size), whereas it has grown by only 27.2% (about 293 kilometers) for a deal at the 90^{th} percentile of the deal size distribution.[55] These findings uncover another limitation of remote communication: Virtual meetings may not be enough for the VCs to strike a deal when they have enormous financial stakes in it. In order to seal such financially vital deals, VCs may insist on a more prudent strategy to meet the entrepreneurs and key employees in person.

[Insert Table 8 Here.]

5 Implications of the death of distance

The death of distance in VC investment has major implications on entrepreneurial finance. We discuss the relationship between in-person meetings and remote communication in the post-pandemic era in Section 5.1. We study the competition among the VCs in Section 5.2 and we examine the regional inequality of entrepreneurial access to VC financing in Section 5.3.

[54] Since the deal size information is missing for some deals, the number of observations in this table is smaller than that in Table 1.

[55] The sample mean and the 90^{th} percentile of the deal size distribution are 37.9 and 100.0 million U.S. dollars, respectively.

5.1 Are in-person meetings still important in the post-pandemic era?

In light of the rising importance of remote communication, one may wonder if on-site visits and in-person meetings are still important in the VC industry in the post-pandemic era. One may also wonder if there is a conflict between the findings on the death of distance in VC investment and the studies showing on-site visits and in-person meetings are important for VC investment decisions (e.g., Tian (2011), Bernstein et al. (2016)). Note that our study is not designed to compare whether remote communication or in-person meetings are more important for the VCs, and the findings on the death of distance are not interpreted as a straight denial of the importance of on-site visits and in-person meetings in the VC industry. Though remote communication and in-person meetings are to some extent substitutable with each other, the two communication methods are presumably not perfect substitutes.[56] In the aftermath of the COVID-19 pandemic, the costs of communicating with the entrepreneurs and monitoring the ventures via remote communication have remarkably declined for the VCs. As a response to such a reduction in the costs of remote communication relative to in-person meetings, the VCs have re-optimized their relative reliance on the two communication methods, but they are unlikely to resort to a corner solution with only one method. To the extent that the persistence and acceleration of the death of distance in 2021 indicate that remote communication may have become more important than the pre-pandemic situation, the VC investment process is unlikely to completely revert to the pre-pandemic regime. On the other hand, our findings also suggest that in-person meetings could still be essential when the quality of the internet infrastructure is low, when the level of information asymmetry between VCs and entrepreneurs is high, and when the deal size is large. Therefore, both remote communication and in-person meetings will probably be indispensable in the post-pandemic era.

Instead of making a horse-racing comparison between the importance of remote communication and in-person meetings, our study aims to investigate how VCs re-optimize their strategies for

[56]Though it is elusive to find any direct and compelling evidence on the elasticity of substitution (EoS) between remote communication and in-person meetings, some studies have provided a related estimate on the EoS between working at home and working at the office. For instance, the EoS between working at home and working at the office is estimated to be 5.0 in Davis et al. (2021). This is suggestive evidence that remote communication and in-person meetings are presumably substitutable with each other, but they are not perfect substitutes. Echoing this finding, a study by the Pew Research Center indicates that 68% of Americans report that digital interactions have been useful for communications, but they are not a complete replacement for in-person connections. See more details in the Pew Research Center report on "The Internet and the Pandemic," September 1, 2021.

communicating with the entrepreneurs, gathering information about the startups and monitoring the ventures, in response to a change in the relative effectiveness and costs of different communication methods. Viewed from this perspective, both our findings and previous studies on geographic proximity have delivered the same message. For instance, Bernstein et al. (2016) find that VCs increase on-site involvement with startup companies when direct flights have reduced the costs of traveling. According to our findings, VCs increase their reliance on remote communication when pandemic-induced innovations have reduced the costs of communicating with the entrepreneurs and monitoring the ventures via online conferences (relative to in-person meetings). In light of this, both studies demonstrate that VCs are agile to adapt to a changing business environment in the sense that they have swiftly transformed and re-optimized their traditional investment processes to seize emerging technological and commercial opportunities.

5.2 Competition among the VCs

As underscored in Petersen and Rajan (2002), investing in private small ventures is challenging because they are not obliged to disclose elaborate information to the public and the investors are confronted with a dearth of public information about such businesses. In addition, the information about such private small ventures tends to be "soft," and, thus, is difficult to collect, store, and communicate with others (Stein (2002)). To acquire information about such private small ventures and monitor such businesses, direct contact with entrepreneurs becomes crucial and local presence or on-site visits are of paramount importance for the investors. In light of this, a VC investor features monopoly power in its local market because it enjoys lower travel and monitoring costs than its competitors located far away from the startups. In small business financing, it is well-documented that local investors wield their market power to extract rents from local businesses (e.g., by spatial price discrimination as documented in Degryse and Ongena (2005)).[57] Our previous findings suggest that enhanced remote communication technology has reduced the costs of communicating with remote entrepreneurs and monitoring their businesses, and, thus, has incentivized the VCs to invest in more distant startups. As a consequence, does the influx of investors from outside

[57] Degryse and Ongena (2005) find that "loan rates decrease with the distance between the firm and the lending bank and increase with the distance between the firm and competing banks."

regions intensify local competition among the VCs? We investigate this question by the deal-level regressions in Table 9 and the city-level regressions in Table 10.

The empirical setup of the regressions in Table 9 is based on equation (1). The dependent variable *1*{*Different country*} in regression (1) equals one if the startup receives an investment from a VC firm located in a foreign country, and zero otherwise.[58] In regression (2)–(4), the dependent variable *1*{*Distance* > *x km*} equals one if the VC firm is located more than x kilometers away from the startup, and zero otherwise. The results in Table 9 indicate that a startup company is more likely to receive financing from foreign VC investors and distant VCs after the COVID-19 pandemic. Compared to the situation in 2017 (the omitted group), regression (1) of Table 9 suggests that the probability for a startup to receive financing from foreign VCs has ratcheted up by 1.8 percentage points in 2020 and 17.6 percentage points in 2021.[59] As a comparison, these effects amount to 7.7% and 74.9% of the mean odds for a startup to receive financing from foreign VCs. According to regression (4) of Table 9, the probability for a startup to receive financing from VCs more than 1,000 kilometers away has grown by 2.8 percentage points in 2020 and 15.3 percentage points in 2021, amounting to 5.9% and 32.2% of the mean odds for a startup to receive financing from these distant VC investors (i.e., those located more than 1,000 kilometers away).

[Insert Table 9 Here.]

Built on the deal-level evidence in Table 9, we examine how the industrial organizational structure of the VC industry evolved in the city-year-level regressions in Table 10. The dependent variable in this table is the city-level Herfindahl-Hirschman index (HHI) of VC investments received by startup companies in each city each year, a proxy of the concentration of the source of VC financing for each city. The dependent variable in regression (1) is the HHI index based on the investment share of individual VC investors. The dependent variable in regression (2) is the HHI index based on the investment share of the cities of the VC investors. We control for the number of deals, the number of startups receiving VC investments, and the number of VC investors in these

[58] The VCs and the startups can be located in different countries when cross-border deals are included and the standard errors are clustered by the countries of the VCs.

[59] Logit regressions (not reported due to space limit) yield similar results. To be specific, the regressions based on the Logit model suggest that the probability for a startup to receive financing from foreign VCs has increased by 2.1 percentage points in 2020 and 18.4 percentage points in 2021.

deals. We also control for country-level GDP growth rate and the number of patent applications via the Patent Cooperation Treaty. We include city fixed effects to control for all time-invariant city-level heterogeneity.

The results in Table 10 suggest that the VC industry has become significantly more competitive after the pandemic. According to regression (1) of Table 10, the HHI of VC investments received by a city has decreased by 0.036 in 2020 (6.7% of the sample mean) and by 0.106 (19.8% of the sample mean) in 2021, compared to the situation in 2017 (the omitted group).[60] After enhanced remote communication technology has spurred VCs to invest in remoter ventures, the influx of investors from outside regions has intensified local competition among the VCs. Though further elaborate evidence is limited (because detailed deal terms are not commonly disclosed), such intensified local competition among the VCs may contribute to curtailing their monopoly power and eroding their spatial rents.

[Insert Table 10 Here.]

5.3 Regional inequality of entrepreneurial access to VC financing

VC financing features a high level of geographic concentration. In the United States, Chen et al. (2010) document that the top three metropolitan areas (i.e., San Francisco, Boston, and New York) account for about one-half of the US-based companies financed by VCs. In China, Beijing and Shanghai alone have attracted about one-half of VC investments. In contrast, entrepreneurs in remote areas are struggling with a paucity of VC financing. Since most VC investors are located in economically advanced regions, the regional inequality of entrepreneurial access to VC financing is in part due to the time and financial costs of long-distance travel. In light of the death of distance in VC investment, one may wonder if the regional inequality of VC financing will be mechanically alleviated as VC funding shifts toward remoter ventures after the pandemic. This is not necessarily true because the death of distance can also be attributed to a reshuffling of VC financing among the economically advanced regions (i.e., VCs in advanced regions may invest in local startups before

[60] Regression (2) of Table 10 yields similar results. According to regression (2), the HHI of VC investments received by a city has decreased by 0.034 in 2020 (6.3% of the sample mean) and by 0.105 (19.5% of the sample mean) in 2021, compared to the situation in 2017 (the omitted group).

COVID-19 and switch to remote startups in other *advanced* regions after the pandemic). Does the death of distance imply that more VC funding has been channeled toward entrepreneurs in disadvantaged regions? We investigate this question in country-level regressions in Table 11 and deal-level regressions in Table 12.

We trace how the national geographic concentration of VC investments evolved in each country in Table 11. The dependent variable in this table is the country-level HHI for the share of VC investments received by each city in each country, a proxy of the geographic concentration of VC financing in a country. We control for a country's population, per capita GDP, GDP growth rate, and the number of patent applications via the Patent Cooperation Treaty, all with a one-year lag. Echoing our previous findings on the death of distance, the results in Table 11 indicate that the geographic distribution of VC investments in a country has become significantly more dispersed after the pandemic. According to the last column of Table 11, the national HHI of VC investments in a country has decreased by 0.037 in 2020 (24.8% of the sample mean) and by 0.044 (29.5% of the sample mean) in 2021, compared to the situation in 2017 (the omitted group).

[Insert Table 11 Here.]

Built on the country-level evidence in Table 11, we examine VC investments made to economically disadvantaged regions in deal-level regressions in Table 12.[61] The empirical setup of the regressions in this table is based on equation (1). The dependent variables in these regressions are dummy variables for startups in economically disadvantaged regions. We adopt three strategies to categorize an economically disadvantaged region in each country: (i) cities receiving fewer than three VC investments in 2019 (i.e., one year before the COVID-19 pandemic), (ii) the bottom 30% cities in a country ranked by VC investments received in 2019, (iii) the bottom 30 cities in a country ranked by VC investments received in 2019.

In regression (1) of Table 12, a city is categorized to be disadvantaged if it receives fewer than three VC investments in 2019. The dependent variable *1{Fewer than 3 investments}* takes the value of one if the startup is located in a disadvantaged city based on this criterion, and zero otherwise. Compared to the situation in 2017 (the omitted group), regression (1) of Table 12 suggests that the

[61] We exclude countries with fewer than three cities receiving VC investments.

probability for a VC to invest in a disadvantaged city has ratcheted up by 1.0 percentage points in 2020 and 2.9 percentage points in 2021.[62] As a comparison, these effects amount to 21.3% and 61.7% of the mean odds for a VC to invest in a disadvantaged city under this classification criterion (i.e., with fewer than three deals).

In regression (2) of Table 12, the dependent variable *1{Bottom 30% cities}* takes the value of one if the startup is located in the bottom 30% cities in its country ranked by VC investments received in 2019, and zero otherwise. Regression (2) of Table 12 suggests that the probability for a VC to invest in the bottom 30% cities in a country (ranked by pre-pandemic VC investments) has risen by 0.5 percentage points in 2020 and 1.3 percentage points in 2021, amounting to 27.8% and 72.2% of the mean odds for a VC to invest in these bottom 30% cities.

In regression (3) of Table 12, the dependent variable *1{Bottom 30 cities}* takes the value of one if the startup is located in the bottom 30 cities in its country ranked by VC investments received in 2019, and zero otherwise. Regression (3) of Table 12 indicates that the probability for a VC to invest in the bottom 30 cities in a country (ranked by pre-pandemic VC investments) has risen by 0.8 percentage points in 2020 and 1.8 percentage points in 2021, amounting to 13.3% and 30.0% of the mean odds for a VC to invest in these bottom 30 cities.

According to the results in Table 12, VCs are significantly more likely to invest in startups located in economically disadvantaged regions after the COVID-19 pandemic. In light of this, the death of distance in VC investment implies that more VC funding has been channeled toward startups in disadvantaged areas. Viewed from this perspective, the COVID-19 pandemic is to some extent a paradoxical blessing instead of a curse for entrepreneurs in disadvantaged regions. As underlined by Albert Einstein, "A crisis can be a real blessing to any person, to any nation. For all crises bring progress." Thanks to the advancement and adoption of remote communication technology spurred by social distancing requirements, online conferences have become a better substitute for in-person meetings, incentivizing VCs to invest in remote ventures in disadvantaged regions. Therefore, removing the geographic barriers to VC investment mitigates the regional

[62] Logit regressions (not reported due to space limit) yield similar results. To be specific, the results based on Logit regressions suggest that the probability for a VC to invest in a disadvantaged city (i.e., receiving fewer than three investments before the pandemic) has increased by 1.9 percentage points in 2020 and 4.8 percentage points in 2021.

inequality of entrepreneurial access to VC financing and democratizes entrepreneurship.

[Insert Table 12 Here.]

6 Conclusion

Unprecedented mobility-restriction policies have been adopted all around the world to combat the COVID-19 pandemic. Based on deal-level evidence of 4,086 venture capital (VC) firms in 49 countries accounting for 90.0% of global GDP, our findings suggest the death of distance in VC investment: VCs invest in more distant ventures during the COVID-19 pandemic in 2020 and such effects persisted and accelerated in 2021. The pandemic-spurred advancement and adoption of remote communication technology has contributed to the death of distance in VC investment. As geographic boundaries of VC investment are shattered after the pandemic, local competition among the VCs has intensified and the regional inequality of entrepreneurial access to VC financing has been mitigated. Resembling the Great Depression and the Great Recession, the Great Lockdown seems to have prompted progressive changes in entrepreneurial finance despite its disruptions. While the post-pandemic period has not been long enough to reach any solid conclusions, we have observed some early suggestive evidence that the changes in VC investment strategies during the Great Lockdown may herald long-lasting transformations in the post-pandemic era.

Nevertheless, our findings have also uncovered the limitations of remote communication when there is poor internet infrastructure, when there is severe information asymmetry between VCs and entrepreneurs, and when the deal size is large. In light of such limitations, regional inequality of entrepreneurial access to VC financing can be further relieved and local competition among the VCs can be further intensified, if public policies can improve the internet infrastructure in economically disadvantaged regions or alleviate the information asymmetry problems for the investors.

While we focus on examining the advancement and adoption of remote communication technology as a potential contributing factor to the death of distance, anecdotal evidence suggests that the reduction in behavioral biases (against virtual meetings) can also be instrumental in spurring such changes in VC investment strategies. After being forced to adapt to remote communication during lockdowns, some VCs and entrepreneurs have overcome their behavioral biases against virtual meetings, and, thus, they continue embracing remote communication after the economy reopened. It would be interesting for future research to further explore the role of behavioral biases against remote communication. Apart from the VCs, how COVID-19 lockdowns affect other financial institutions (e.g., banks, hedge funds, etc.) is also a valuable topic for future research.

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Figure 1: **Distribution of distance between VCs and startup companies**

We plot the distribution of the distance between VCs and startup companies in this figure. The horizontal axis is the VC-startup distance and the vertical axis is the cumulative distribution function. We compare the VC-startup distance distribution during the two years after the pandemic (i.e., 2020–2021) with its counterpart during the two years before the pandemic (i.e., 2018–2019).

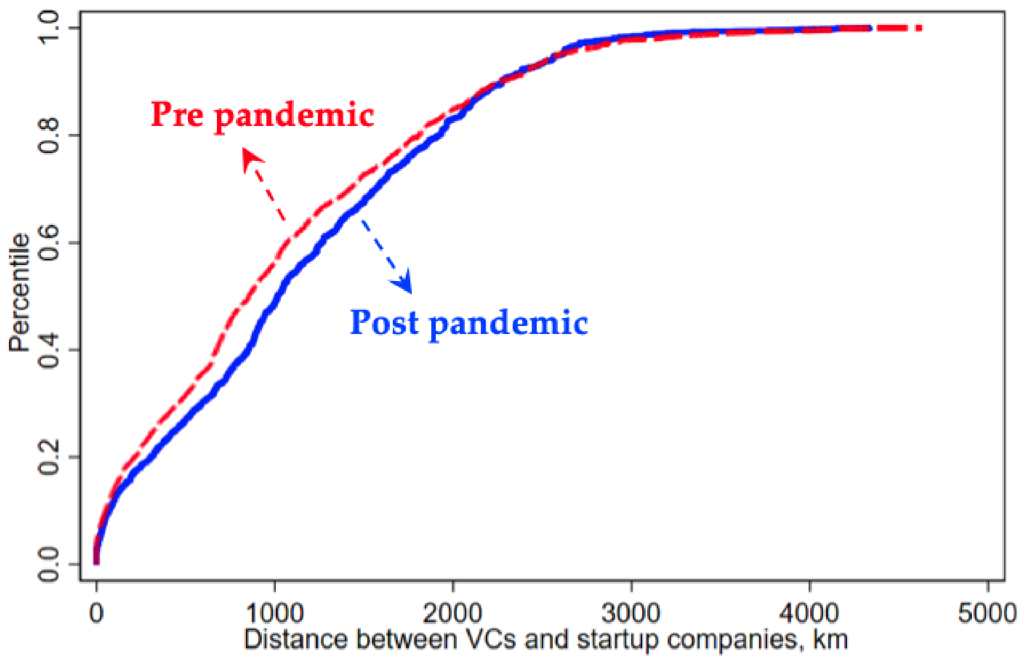


Figure 2: **VC-Startup distance by countries**

In this figure, we plot the average distance between VCs and startup companies in each country during the two years after the pandemic (i.e., 2020–2021) against the average VC-startup distance during the two years before the pandemic (i.e., 2018–2019). To visualize the relative importance of each country, the size of the circles in this figure is proportional to the number of deals in each country.

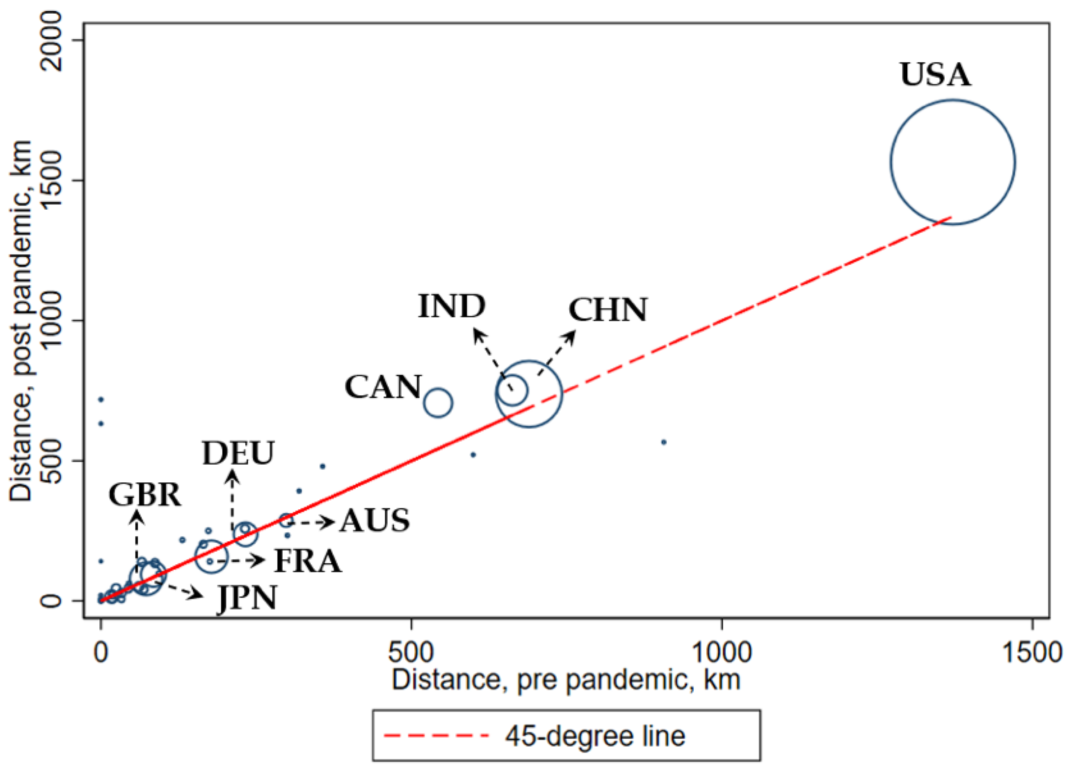


Figure 3: **VC-Startup distance by industries**

In this figure, we plot the average distance between VCs and startup companies in each industry during the two years after the pandemic (i.e., 2020–2021) against the average VC-startup during the two years before the pandemic (i.e., 2018–2019). To visualize the relative importance of each country, the size of the circles in this figure is proportional to the number of deals in each industry.

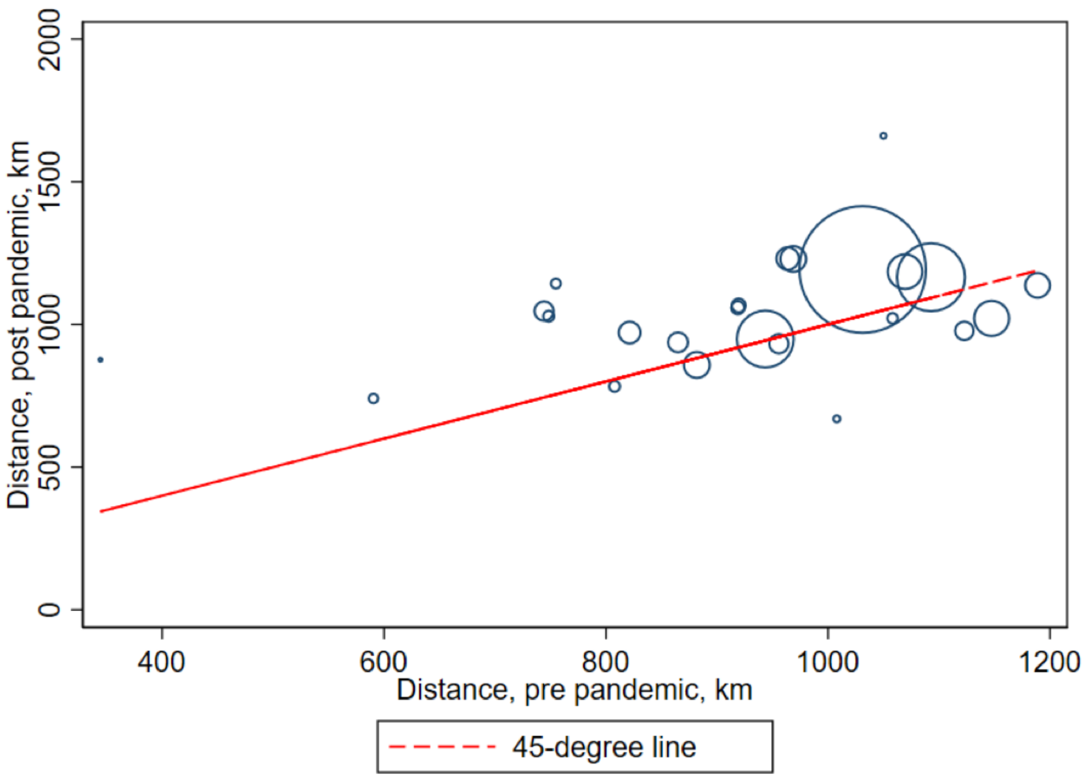


Figure 4: **Staggered lockdowns across different regions in China**

This figure visualizes the lockdown and reopening periods in each province of China. A province is classified to be under lockdown when level-I or level-II government emergency response is effective. Reopening refers to the period when the lockdown restrictions have been lifted (i.e., when level-II government emergency response has been phased out). The solid lines and dashed lines represent the lockdown and reopening periods, respectively.

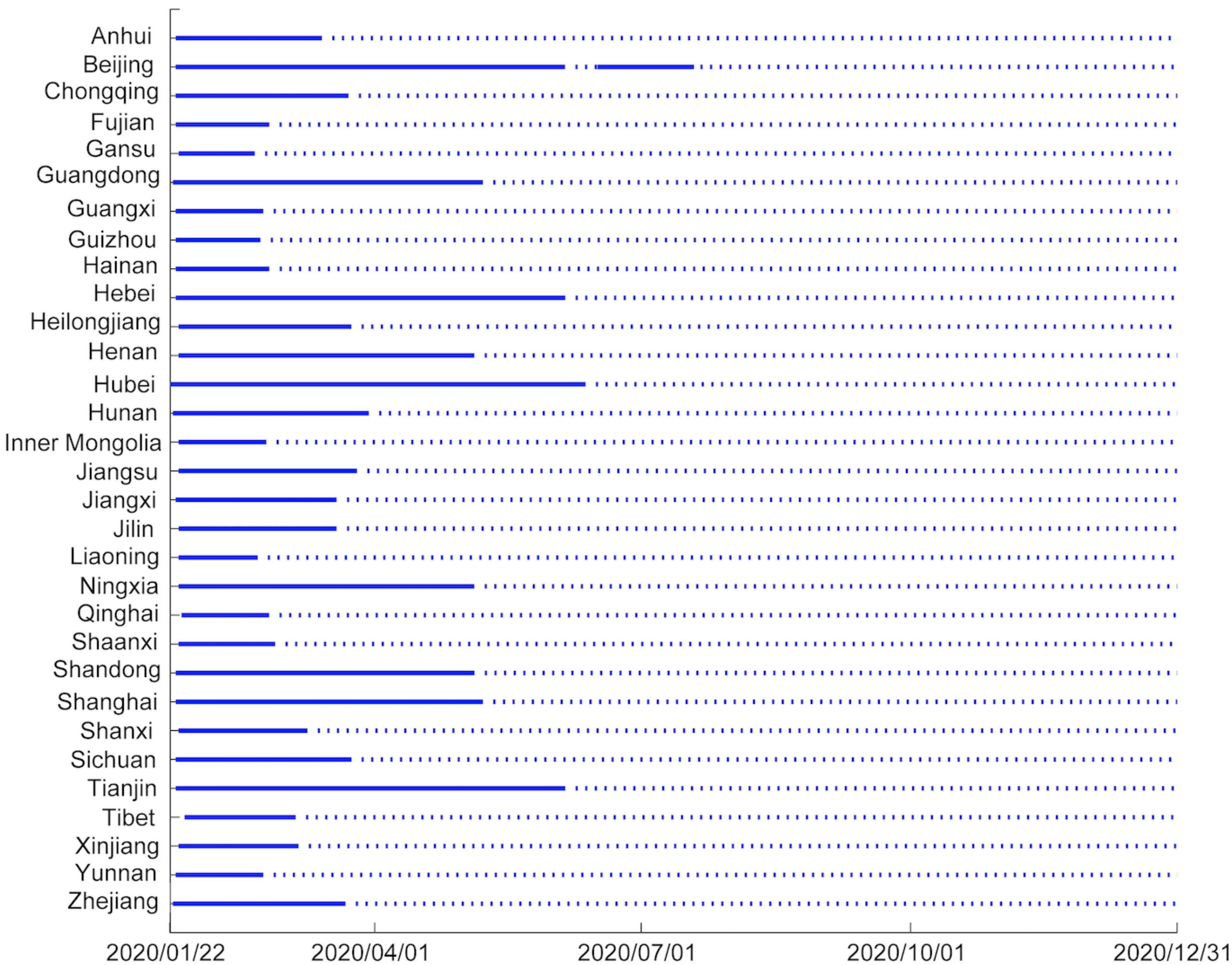


Table 1: COVID-19 and VC-startup distance

In this table, we examine how the distance between VCs and startup companies evolved in recent years. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2	0.315***	0.293***	0.297***	0.297***
	(0.089)	(0.090)	(0.090)	(0.090)
COVID1	0.127**	0.119**	0.118**	0.114**
	(0.056)	(0.054)	(0.055)	(0.054)
1{2019}	0.021	0.023	0.024	0.023
	(0.057)	(0.057)	(0.059)	(0.059)
1{2018}	0.071	0.072	0.069	0.068
	(0.055)	(0.056)	(0.056)	(0.056)
Observations	76,527	76,527	76,527	76,527
Adjusted R-squared	0.290	0.291	0.291	0.292
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

Table 2: COVID-19 Mobility Restriction Stringency

We assess the role of government restrictions on human mobility in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *Restriction stringency* is a country-level measure of the government mobility restriction stringency in the OxCGRT database. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2 × *Restriction stringency*	0.580**	0.484**	0.462**	0.459**
	(0.231)	(0.213)	(0.214)	(0.215)
COVID1 × *Restriction stringency*	0.714**	0.647**	0.650**	0.638**
	(0.351)	(0.311)	(0.309)	(0.302)
COVID2	-2.063**	-1.690*	-1.595*	-1.585*
	(0.988)	(0.913)	(0.922)	(0.926)
COVID1	-2.774*	-2.510*	-2.522**	-2.477**
	(1.421)	(1.259)	(1.250)	(1.223)
1{2019}	0.021	0.023	0.024	0.023
	(0.056)	(0.056)	(0.058)	(0.058)
1{2018}	0.072	0.073	0.070	0.069
	(0.054)	(0.055)	(0.055)	(0.055)
Observations	76,527	76,527	76,527	76,527
Adjusted R-squared	0.290	0.291	0.292	0.292
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

TABLE 3: COVID-19 MOBILITY RESTRICTION POLICIES

We assess the role of specific mobility restriction polices in this table. All regressions include VC, industry, round, and quarter fixed effects. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. ***, ** , * denotes significance at the 1%, 5%, and 10% level.

		Distance	
Panel A	*Cancel public events*	*Restrictions on gatherings*	*Travel restrictions*
COVID2 × *Restriction policy*	0.537***	0.463**	0.516***
	(0.132)	(0.215)	(0.146)
COVID1 × *Restriction policy*	0.558***	0.254*	0.542**
	(0.167)	(0.138)	(0.263)
COVID2	-0.287*	-0.440	-0.211
	(0.158)	(0.344)	(0.148)
COVID1	-0.495***	-0.240	-0.382
	(0.171)	(0.183)	(0.244)
1{2019}	0.022	0.024	0.036
	(0.059)	(0.061)	(0.057)
1{2018}	0.068	0.070	0.076
	(0.056)	(0.056)	(0.054)
Observations	76,527	76,527	76,527
Adjusted R-squared	0.292	0.292	0.292
VC, industry, round, and quarter FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

		Distance	
Panel B	*Public transport closings*	*Workplace closings*	*Stay at home*
COVID2 × *Restriction policy*	0.390*	0.443***	0.325***
	(0.224)	(0.091)	(0.090)
COVID1 × *Restriction policy*	0.478***	0.608***	0.556***
	(0.120)	(0.170)	(0.108)
COVID2	0.095	-0.217	0.020
	(0.147)	(0.150)	(0.119)
COVID1	-0.158*	-0.574***	-0.358***
	(0.092)	(0.195)	(0.107)
1{2019}	0.009	0.025	0.029
	(0.063)	(0.059)	(0.053)
1{2018}	0.064	0.072	0.073
	(0.057)	(0.055)	(0.053)
Observations	76,527	76,527	76,527
Adjusted R-squared	0.292	0.292	0.292
VC, industry, round, and quarter FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

Table 4: VC Investment during lockdowns and reopening

In this table, we track the changes in VC investment decisions during the lockdowns and after the economy reopens. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The *COVID* dummy takes the value of one for VC investments made in 2020 and equals zero for investments made in 2019. *Lockdown* equals one if either the VC or the startup is facing a lockdown and zero otherwise. *Reopen* equals to one if the lockdown is lifted for both the VC and the startup and zero otherwise. *Before* equals one for the period four weeks before the lockdown and zero otherwise. The omitted period is from January 1, 2020 to the date when *Before* switches to the value of one. The control variables are delineated in Section (3.2). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

		Distance	
	(1)	(2)	(3)
COVID × *Before*	-0.077	-0.081	-0.046
	(0.234)	(0.233)	(0.234)
COVID × *Lockdown*	0.228*	0.222*	0.223*
	(0.117)	(0.117)	(0.118)
COVID × *Reopen*	0.180*	0.171*	0.185*
	(0.102)	(0.102)	(0.103)
Before	1.415*	1.536*	1.502*
	(0.792)	(0.784)	(0.797)
Lockdown	2.059**	2.157**	2.182**
	(0.949)	(0.942)	(0.949)
Reopen	0.625	0.701	0.699
	(0.954)	(0.947)	(0.954)
Observations	10,622	10,622	10,622
Adjusted R-squared	0.271	0.273	0.274
VC fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes
Round fixed effects	No	No	Yes
Control	Yes	Yes	Yes

Table 5: Lockdown proxies based on human mobility level

The empirical setup of the regressions in this table is the same as that in Table 4, except that *Lockdown* and *Reopen* in this table are based on the human mobility level. The end of the lockdown period corresponds to the trough mobility date in a city (i.e., the date when this city hit its lowest level of human mobility in 2020). The reopening phase in this table refers to the period between the trough mobility date and the end of the year. All other variables are the same as those in Table 4. The control variables are delineated in Section (3.2). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance		
	(1)	(2)	(3)
COVID × *Before*	0.009	0.008	0.045
	(0.239)	(0.239)	(0.241)
COVID × *Lockdown*	0.565**	0.526*	0.503*
	(0.278)	(0.278)	(0.279)
COVID × *Reopen*	0.180**	0.172*	0.170*
	(0.088)	(0.088)	(0.090)
Before	-0.848	-0.784	-0.837
	(0.838)	(0.838)	(0.845)
Lockdown	-2.193**	-2.118**	-2.058*
	(1.056)	(1.055)	(1.060)
Reopen	-3.350***	-3.318***	-3.270***
	(1.071)	(1.070)	(1.074)
Observations	10,020	10,020	10,020
Adjusted R-squared	0.232	0.234	0.235
VC fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes
Round fixed effects	No	No	Yes
Control	Yes	Yes	Yes

Table 6: Internet infrastructure

We assess the role of the internet infrastructure in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *Internet latency* is the greater value of the internet latency of the VC and the startup in each deal. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2 × *Internet latency*	-0.666*	-0.598**	-0.570*	-0.570*
	(0.288)	(0.246)	(0.262)	(0.265)
COVID1 × *Internet latency*	-1.129**	-1.029***	-1.026***	-1.019***
	(0.347)	(0.278)	(0.275)	(0.282)
COVID2	2.778**	2.507**	2.419**	2.417**
	(0.946)	(0.782)	(0.823)	(0.832)
COVID1	3.957**	3.614***	3.600***	3.573***
	(1.161)	(0.916)	(0.906)	(0.933)
1{2019}	0.066	0.071	0.071	0.071
	(0.069)	(0.071)	(0.071)	(0.071)
1{2018}	0.083	0.088	0.082	0.082
	(0.052)	(0.054)	(0.054)	(0.054)
Observations	55,057	55,057	55,057	55,057
Adjusted R-squared	0.284	0.285	0.286	0.286
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

Table 7: Information asymmetry

We assess the role of information asymmetry in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). All regressions include VC fixed effects, industry fixed effects, round fixed effects, and quarter fixed effects. Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

	Distance		
	(1)	(2)	(3)
COVID2 × *R&D intensity*	-0.473*		
	(0.261)		
COVID1 × *R&D intensity*	-0.575**		
	(0.238)		
COVID2 × *Market/book ratio*		-0.059***	
		(0.016)	
COVID1 × *Market/book ratio*		-0.050***	
		(0.015)	
COVID2 × *Asset tangibility*			0.380**
			(0.180)
COVID1 × *Asset tangibility*			0.662***
			(0.226)
COVID2	0.367**	0.480***	0.235*
	(0.157)	(0.144)	(0.121)
COVID1	0.208**	0.275***	0.027
	(0.079)	(0.086)	(0.042)
1{2019}	0.020	0.021	0.019
	(0.062)	(0.062)	(0.062)
1{2018}	0.078	0.078	0.078
	(0.054)	(0.054)	(0.054)
Observations	74,904	74,904	74,904
Adjusted R-squared	0.293	0.293	0.293
VC, industry, round, and quarter FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

Table 8: Deal size

We assess the role of deal size in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *Deal size* in regression (1) is the amount of VC investments (in natural logarithm). We also report the results based on the real value of VC investments in regression (2). All regressions include VC fixed effects, industry fixed effects, round fixed effects, and quarter fixed effects. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. ***, ** , * denotes significance at the 1%, 5%, and 10% level.

	Distance	
	Nominal investment	*Real investment*
	(1)	(2)
COVID2 × *Deal size*	-0.0657***	-0.0657***
	(0.0159)	(0.0159)
COVID1 × *Deal size*	-0.0395*	-0.0396*
	(0.0229)	(0.0229)
COVID2	0.5747***	0.2625**
	(0.1420)	(0.1013)
COVID1	0.2146*	0.0283
	(0.1089)	(0.0532)
1{2019}	0.0273	0.0267
	(0.0589)	(0.0594)
1{2018}	0.0770	0.0766
	(0.0614)	(0.0617)
Deal size	-0.0173	-0.0175
	(0.0212)	(0.0213)
Observations	65,671	65,671
Adjusted R-squared	0.3087	0.3087
VC, industry, round, and quarter FE	Yes	Yes
Control	Yes	Yes

Table 9: Investments received from distant VCs

The dependent variable *1{Different country}* in regression (1) equals one if the startup receives an investment from a VC firm located in a foreign country, and zero otherwise. In regression (2)–(4), the dependent variable *1{Distance > x km}* equals one if the VC firm is located more than x kilometers away from the startup, and zero otherwise. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. All regressions include VC fixed effects, industry fixed effects, round fixed effects, and quarter fixed effects. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

	1{Different country}	*1{Distance > 100 km}*	*1{Distance > 500 km}*	*1{Distance > 1000 km}*
	(1)	(2)	(3)	(4)
COVID2	0.176*	0.133**	0.147**	0.153**
	(0.094)	(0.058)	(0.060)	(0.067)
COVID1	0.018***	0.024***	0.027***	0.028***
	(0.005)	(0.009)	(0.008)	(0.008)
1{2019}	0.003	0.004	0.009	0.006
	(0.025)	(0.011)	(0.010)	(0.008)
1{2018}	-0.001	0.009	0.010	0.009
	(0.011)	(0.009)	(0.007)	(0.005)
Observations	101,307	101,307	101,307	101,307
Adjusted R-squared	0.423	0.233	0.246	0.249
VC, industry, round, and quarter FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes

Table 10: Competition among the VCs

We examine how the industrial organizational structure of the VC industry evolved in the city-year-level regressions in this table. The dependent variable in this table is the city-level Herfindahl-Hirschman index (HHI) of VC investments received by startup companies in each city each year, a proxy of the concentration of the source of VC financing for each city. The dependent variable in regression (1) is the HHI index based on the investment share of individual VC investors. The dependent variable in regression (2) is the HHI index based on the investment share of the cities of the VC investors. The control variables are delineated in Section (5.2). We include the city fixed effects in both regressions. Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	HHI for the concentration of the source of VC financing	
	HHI by individual investors	*HHI by investor cities*
	(1)	(2)
COVID2	-0.106**	-0.105**
	(0.042)	(0.043)
COVID1	-0.036**	-0.034**
	(0.015)	(0.015)
1{2019}	-0.024	-0.023
	(0.015)	(0.015)
1{2018}	-0.010	-0.009
	(0.013)	(0.013)
Observations	5,528	5,528
Adjusted R-squared	0.548	0.550
City fixed effects	Yes	Yes
Control	Yes	Yes

Table 11: Geographic concentration of VC financing

We trace how the geographic concentration of VC investments in a country evolved in country-year-level regressions in this table. The dependent variable in this table is the country-level HHI for the share of VC investments received by each city in each country, a proxy of the geographic concentration of VC financing in a country. The control variables are delineated in Section (5.3). We include the country fixed effects in all regressions. Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	HHI for VC geographic concentration		
	(1)	(2)	(3)
COVID2	-0.032**	-0.044*	-0.044*
	(0.014)	(0.025)	(0.026)
COVID1	-0.038***	-0.037***	-0.037***
	(0.013)	(0.013)	(0.013)
1{2019}	-0.020	-0.019	-0.019
	(0.015)	(0.015)	(0.015)
1{2018}	-0.013	-0.011	-0.011
	(0.014)	(0.014)	(0.014)
GDP pc	1.203	1.282	1.289
	(2.330)	(2.339)	(2.357)
Population	0.546	0.349	0.334
	(0.358)	(0.446)	(0.454)
GDP growth		-0.002	-0.002
		(0.003)	(0.003)
Innovation output			0.017
			(0.071)
Observations	172	172	172
Adjusted R-squared	0.804	0.802	0.801
Country fixed effects	Yes	Yes	Yes

Table 12: VC Investment in disadvantaged regions

We assess VC investments made to economically disadvantaged regions in this table. The dependent variables in these regressions are dummy variables for startups in economically disadvantaged regions. We adopt three strategies to categorize a disadvantaged region in each country. In regression (1), a city is categorized to be disadvantaged if it receives fewer than three VC investments in 2019 (i.e., one year before the COVID-19 pandemic). In regression 2 (3), a city is categorized to be disadvantaged if it is among the bottom 30% cities (bottom 30 cities) in its country ranked by VC investments received in 2019. The control variables are delineated in Section (2.2). All regressions include VC fixed effects, industry fixed effects, round fixed effects, and quarter fixed effects. Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	1{Disadvantaged region}		
	1{Fewer than 3 investments}	*1{Bottom 30% cities}*	*1{Bottom 30 cities}*
	(1)	(2)	(3)
COVID2	0.029***	0.013***	0.018**
	(0.007)	(0.004)	(0.007)
COVID1	0.010***	0.005**	0.008*
	(0.003)	(0.002)	(0.004)
1{2019}	0.011	0.006	0.007
	(0.012)	(0.005)	(0.007)
1{2018}	0.004	0.003	0.004
	(0.003)	(0.002)	(0.003)
Observations	71,230	71,230	71,230
Adjusted R-squared	0.148	0.102	0.796
VC, industry, round, and quarter FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

Appendix

Table A1: Variable Definitions

Variable	Definition
Distance	Natural logarithm of one plus the distance between VCs and startups
COVID2	A dummy variable for VC investments made in 2021
COVID1	A dummy variable for VC investments made in 2020
1{2019}	A dummy variable for VC investments made in 2019
1{2018}	A dummy variable for VC investments made in 2018
Restriction stringency	A country-level measure of the stringency of mobility restrictions
Internet latency	The greater value of the internet latency faced by VCs and startups
R&D intensity	R&D-to-assets ratio, industry-level proxy
Market/book ratio	Ratio of the sum of the market value of equity and book value of debt to the sum of the book value of debt and equity, industry-level proxy
Asset tangibility	Net value of property, plant, and equipment divided by the book value of assets, industry-level proxy
Deal size	Natural logarithm of the amount of VC investment
1{Different country}	Equals one if the startup receives an investment from a foreign VC
1{Distance > 100 km}	Equals one if the VC is more than 100 km away from the startup
1{Distance > 500 km}	Equals one if the VC is more than 500 km away from the startup
1{Distance > 1000 km}	Equals one if the VC is more than 1000 km away from the startup
HHI by individual investors	City-level HHI of VC investments received by startups in each city, based on the investment share of individual VC investors
HHI by investor cities	City-level HHI of VC investments received by startups in each city, based on the investment share of the cities of the VC investors
HHI of VC geographic concentration	Country-level HHI for the share of VC investments received by each city
1{Fewer than 3 investments}	A dummy variable for startups in disadvantaged regions, a city is categorized to be disadvantaged if it receives fewer than three VC investments
1{Bottom 30% cities}	A dummy variable for startups in disadvantaged regions, a city is categorized to be disadvantaged if it is among the bottom 30% cities in its country ranked by VC investments received
1{Bottom 30 cities}	A dummy variable for startups in disadvantaged regions, a city is categorized to be disadvantaged if it is among the bottom 30 cities in its country ranked by VC investments received
Lockdown	Equals one if either the VC firm or the startup company is facing a lockdown and zero otherwise
Before	Equals one for the period four weeks before the lockdown restriction is imposed and zero otherwise
Reopen	Equals one if the lockdown restriction is lifted for both the VC firm and the startup company and zero otherwise
Innovation Output	Natural logarithm of one plus the number of patents

Table A2: Descriptive Statistics

We provide the deal-level summary statistics in this table. *Distance* in this table refers to the distance between VCs and startup companies, expressed in terms of kilometers (km). *Internet latency* refers to the greater value of the internet latency faced by the VC and the startup in each deal, expressed in terms of milliseconds (ms). All potentially unbounded variables are winsorized at the 1% extremes unless otherwise specified.

	Mean	Standard Deviation	Min	Median	Max	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Distance, km	1,078	1,464	0	298	4,342	76,527
VC age	15.67	14.00	0	12	73	76,527
GDP growth, %	1.172	3.545	-9.396	2.161	6.947	76,527
Restriction stringency	61.01	6.009	48.84	57.72	71.28	76,527
Workplace closings	1.900	0.377	1.436	1.644	2.674	76,527
Cancel public events	1.649	0.195	1.085	1.540	1.951	76,527
Restrictions on gatherings	3.745	0.419	1.307	3.836	4.000	76,527
Public transport closings	0.931	0.197	0.011	1.000	1.373	76,527
Stay at home	1.423	0.613	0.482	1.170	2.608	76,527
Travel restrictions	1.454	0.313	0.219	1.455	2.000	76,527
Internet latency, ms	27.04	3.40	17.75	27.50	37.50	55,057
R&D intensity	0.166	0.0935	0	0.183	0.490	74,904
Asset tangibility	0.129	0.0863	0.027	0.0815	0.558	74,904
Market/book ratio	3.198	1.111	-0.026	3.009	5.537	74,904

Internet appendix

Internet appendix for "The Death of Distance? COVID-19 Lockdown and Venture Capital Investment

Figure IA1: **Global distribution of VC investments**

This figure visualizes the global distribution of domestic VC investments (i.e., investments made from VCs to startups in the same country). Darker regions in this figure indicate a higher level of VC investments.

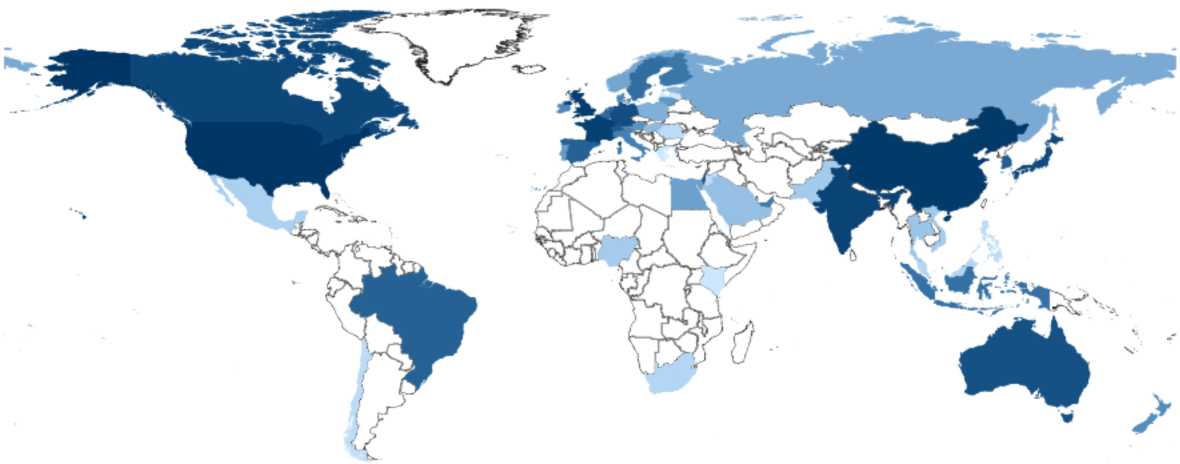
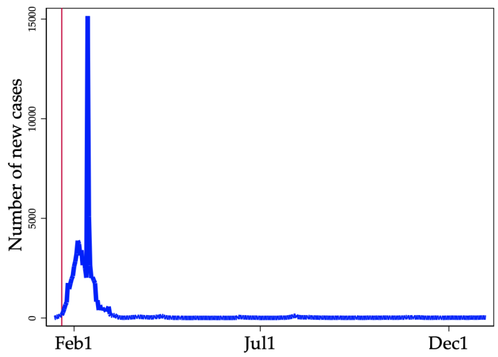
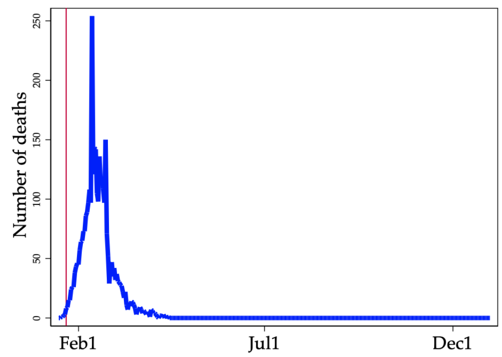


Figure IA2: **Number of COVID-19 cases and deaths in China**

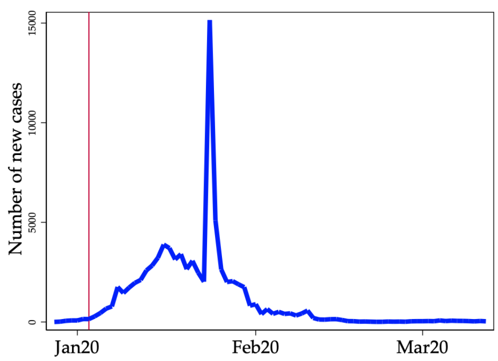
Figure IA2a and IA2b track the number of new COVID-19 cases and the number of deaths from COVID-19 in China in 2020. To highlight the peak of the COVID-19 pandemic in 2020, we zoom in the first quarter of 2020 in Figure IA2c and IA2d. The red vertical line in each figure marks the first lockdown in China.



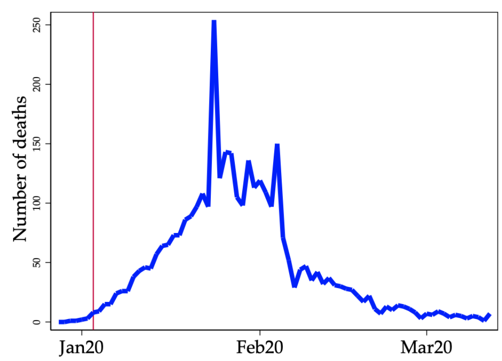
(a) Number of New Cases



(b) Number of Deaths



(c) Number of New Cases, Q1



(d) Number of Deaths, Q1

Figure IA3: **Passenger flows in China**

We track the monthly passenger flows in China in recent years in this figure. The statistics on passenger flows account for all transportation methods and are expressed in terms of the number of trips. The data on passenger flows were sourced from China Railway Corporation, the Ministry of Transport, Civil Aviation Administration, China Petroleum and Natural Gas Corporation Group, China Petrochemical Corporation Group, and the divisions of vehicle management.

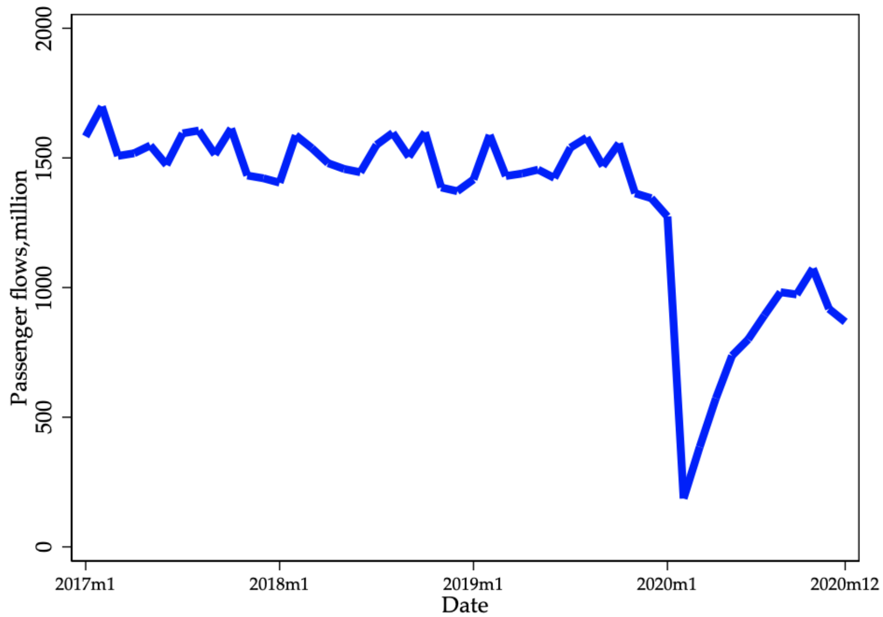


Table IA1: COVID-19 and VC-startup distance, alternative time fixed effects

While we incorporate quarter fixed effects in our baseline estimations, we also report the results based on month fixed effects in regression (1) and day fixed effects in regression (2) of this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. $1\{2018\}$ and $1\{2019\}$ are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). All regressions include VC, industry, and round fixed effects. Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance	
	(1)	(2)
COVID2	0.298***	0.285***
	(0.090)	(0.100)
COVID1	0.113**	0.085*
	(0.054)	(0.043)
$1\{2019\}$	0.023	0.005
	(0.059)	(0.066)
$1\{2018\}$	0.068	0.064
	(0.056)	(0.063)
Observations	76,527	76,527
Adjusted R-squared	0.292	0.293
VC, industry, and round FE	Yes	Yes
Month fixed effects	Yes	No
Day fixed effects	No	Yes
Control	Yes	Yes

Table IA2: COVID-19 and VC-startup distance, startups companies founded before the pandemic

We focus on startup companies founded before the COVID-19 pandemic in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2	0.276***	0.258***	0.269***	0.271***
	(0.077)	(0.086)	(0.087)	(0.084)
COVID1	0.091**	0.086*	0.085*	0.079*
	(0.042)	(0.043)	(0.045)	(0.046)
1{2019}	0.014	0.018	0.020	0.018
	(0.051)	(0.052)	(0.054)	(0.054)
1{2018}	0.064	0.066	0.063	0.061
	(0.054)	(0.055)	(0.055)	(0.055)
Observations	54,877	54,877	54,877	54,877
Adjusted R-squared	0.298	0.299	0.300	0.300
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

Table IA3: COVID-19 and VC-startup distance, lead VC investors

We focus on deals made by the lead VC investors in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2	0.979*	0.957*	0.959*	0.959*
	(0.562)	(0.562)	(0.563)	(0.562)
COVID1	0.218***	0.208***	0.204***	0.202***
	(0.074)	(0.066)	(0.066)	(0.065)
1{2019}	-0.109	-0.120	-0.125	-0.124
	(0.112)	(0.113)	(0.114)	(0.113)
1{2018}	0.064	0.058	0.053	0.055
	(0.059)	(0.059)	(0.059)	(0.059)
Observations	23,665	23,665	23,665	23,665
Adjusted R-squared	0.238	0.239	0.239	0.239
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

Table IA4: COVID-19 and VC-startup distance, first-round investments

We focus on the first-round investments received by the startups in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2	0.580***	0.554***	0.557***	0.547***
	(0.149)	(0.150)	(0.147)	(0.145)
COVID1	0.282***	0.270***	0.272***	0.260***
	(0.099)	(0.099)	(0.097)	(0.094)
1{2019}	0.107	0.102	0.106	0.102
	(0.067)	(0.066)	(0.064)	(0.064)
1{2018}	0.044	0.044	0.046	0.045
	(0.089)	(0.089)	(0.088)	(0.089)
Observations	30,178	30,178	30,178	30,178
Adjusted R-squared	0.281	0.283	0.283	0.283
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

TABLE IA5: COVID-19 AND VC-STARTUP DISTANCE, INCLUDING CROSS-BORDER DEALS

We include cross-border deals in the regressions in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance			
	(1)	(2)	(3)	(4)
COVID2	1.019**	1.005**	1.011**	1.009**
	(0.485)	(0.491)	(0.491)	(0.491)
COVID1	0.154**	0.148**	0.148**	0.143**
	(0.062)	(0.061)	(0.061)	(0.060)
1{2019}	0.021	0.018	0.020	0.019
	(0.105)	(0.104)	(0.104)	(0.103)
1{2018}	0.049	0.050	0.049	0.048
	(0.059)	(0.059)	(0.059)	(0.060)
Observations	101,307	101,307	101,307	101,307
Adjusted R-squared	0.273	0.274	0.274	0.274
VC fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Round fixed effects	No	No	Yes	Yes
Quarter fixed effects	No	No	No	Yes
Control	Yes	Yes	Yes	Yes

Table IA6: COVID-19 and the number of VC investments

We examine how the number of investments made by the VCs evolved in VC-year-level regressions in this table. The dependent variable is the natural logarithm of the number of VC investments. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. $1\{2018\}$ and $1\{2019\}$ are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. The control variables are delineated in Section (2.2). VC fixed effects are included in regression (2). Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Number of deals	
	(1)	(2)
COVID2	0.100	0.292**
	(0.095)	(0.144)
COVID1	0.029	0.004
	(0.037)	(0.068)
$1\{2019\}$	-0.007	0.021
	(0.036)	(0.039)
$1\{2018\}$	0.004	0.026
	(0.010)	(0.029)
Observations	15,159	15,159
Adjusted R-squared	0.041	0.667
VC fixed effects	No	Yes
Control	Yes	Yes

Table IA7: COVID-19 and VC-startup distance, heterogeneity by changes in the number of investments

We interact the COVID indicators with the post-pandemic changes in the number of VC investments in this table. The dependent variable is the natural logarithm of one plus the distance between VCs and startup companies. The dummy variable *COVID1* takes the value of one for VC investments made in 2020 and equals zero otherwise. *COVID2* is a dummy variable for VC investments made in 2021. *1{2018}* and *1{2019}* are dummy variables for investments made in 2018 and 2019, respectively, and the omitted year is 2017. *Change in number of deals* refers to the change in the number of VC investments relative to 2019 and *Percentage change in number of deals* is the percentage change. *Number of deals* refers to the number of investments made by the VCs. The control variables are delineated in Section (2.2). All regressions include VC, industry, round, and quarter fixed effects. Standard errors are clustered at the country level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance		
	(1)	(2)	(3)
COVID2 × *Change in number of deals*	0.010		
	(0.013)		
COVID1 × *Change in number of deals*	0.005		
	(0.012)		
COVID2 × *Percentage change in number of deals*		-0.006	
		(0.038)	
COVID1 × *Percentage change in number of deals*		0.018	
		(0.036)	
COVID2 × *Number of deals*			0.003
			(0.004)
COVID1 × *Number of deals*			0.003
			(0.003)
COVID2	0.223*	0.273**	0.177
	(0.130)	(0.106)	(0.139)
COVID1	0.104*	0.094**	0.050
	(0.053)	(0.046)	(0.053)
Observations	76,527	72,363	76,527
Adjusted R-squared	0.292	0.287	0.292
VC, industry, round, and quarter FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

Table IA8: VC Investment during lockdowns and reopening

The empirical setup of the regressions in this table is the same as that in Table 4, except that the time lag of VC investment is taken to be fifty days in this table. *Lockdown* equals one if either the VC or the startup is facing a lockdown and zero otherwise. *Reopen* equals to one if the lockdown is lifted for both the VC and the startup and zero otherwise. *Before* equals one for the period four weeks before the lockdown and zero otherwise. The omitted period is from January 1, 2020 to the date when *Before* switches to the value of one. The control variables are delineated in Section (3.2). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance		
	(1)	(2)	(3)
COVID × *Before*	0.249	0.269	0.299
	(0.248)	(0.248)	(0.249)
COVID × *Lockdown*	0.222*	0.206*	0.196*
	(0.115)	(0.115)	(0.116)
COVID × *Reopen*	0.170*	0.169*	0.185*
	(0.096)	(0.097)	(0.098)
Before	0.856	0.986	0.938
	(1.381)	(1.391)	(1.397)
Lockdown	2.172	2.269	2.278
	(1.579)	(1.587)	(1.593)
Reopen	0.749	0.839	0.827
	(1.581)	(1.589)	(1.595)
Observations	10,622	10,622	10,622
Adjusted R-squared	0.270	0.273	0.274
VC fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes
Round fixed effects	No	No	Yes
Control	Yes	Yes	Yes

Table IA9: Lockdowns based on human mobility level, different reopening phases

The empirical setup of the regressions in this table is the same as that in Table 5, except that the reopening process is divided into two phases. Early-stage reopening refers to the period between the trough mobility date and the half-recovery date (i.e., the date when the human mobility level in a city in 2020 has restored at least one-half of its previous level in 2019). Late-stage reopening phase refers to the period between the half-recovery date and the end of the year. All other variables are the same as those in Table 5. The control variables are delineated in Section (3.2). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance		
	(1)	(2)	(3)
COVID × *Before*	0.023	0.026	0.060
	(0.240)	(0.239)	(0.241)
COVID × *Lockdown*	0.621**	0.583**	0.560**
	(0.278)	(0.278)	(0.279)
COVID × *Early Reopen*	0.385	0.298	0.278
	(0.458)	(0.458)	(0.462)
COVID × *Late Reopen*	0.164*	0.159*	0.157*
	(0.089)	(0.089)	(0.091)
Before	-0.801	-0.742	-0.795
	(0.839)	(0.839)	(0.846)
Lockdown	-2.188**	-2.117**	-2.059*
	(1.057)	(1.056)	(1.061)
Early Reopen	-4.614***	-4.534***	-4.460***
	(1.122)	(1.120)	(1.126)
Late Reopen	-2.627**	-2.600**	-2.565**
	(1.078)	(1.077)	(1.081)
Observations	10,020	10,020	10,020
Adjusted R-squared	0.235	0.238	0.239
VC fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes
Round fixed effects	No	No	Yes
Control	Yes	Yes	Yes