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# The Reallocation Effects of COVID-19: Evidence from Venture Capital Investments around the World

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# *The Reallocation Effects of COVID-19: Evidence from Venture Capital Investments around the World* *

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**Abstract**
We examine possible reallocation effects on venture capital (VC) investment due to the spread of COVID-19 around the globe. Exploiting the staggered nature of the pandemic and transaction-level data, we empirically document a shift of venture capital towards deals in pandemic-related categories. A difference-in-differences analysis estimates significant increases in invested amount and number of deals in such categories. We further highlight several heterogenous effects related to the experience of VC investors, their organizational form, and country of origin. Our results underscore the link between the spread of the pandemic and the functioning of the VC market around the world.

**Keywords**: Venture Capital, Investment, COVID-19, Healthcare, Pandemic.

**JEL Classification:** G24, F21, D81, E22, E44.



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## 1. Introduction

The outbreak of the COVID-19 pandemic and the resultant social distancing measures that restricted business activity and movement of people caused a sudden and unprecedented stop to economic activity and a globally synchronized contraction in GDP (IMF, 2020). According to the World Economic Outlook released by the International Monetary Fund in June 2020, the annualized growth of global real GDP was projected at -4.9%, compared to a +3.3% projection released in January 2020 just before the global spread of the pandemic. In advanced economies, the contraction was even larger.[2] It is widely believed, however, that the economic effects of the pandemic would not be restricted to a severe recessionary twin supply-demand shock but would also trigger broad reallocations of real and financial resources across sectors and firms (Barrero et al., 2020; OECD, 2020).

As the coronavirus began to spread across the world, investors saw substantial changes in the profitability and growth prospects of firms. The uncertainty generated by the trajectory of the pandemic and the global economic slowdown strongly affected stock returns, leading to a more cautious investment approach and a reduction in available capital for many sectors of the economy (Alfaro et al., 2020; Baker et al., 2020a, 2020b). At the same time, investment opportunities related to the fight against the virus or in industries that could shape the post-pandemic world emerged. This signaled the potential start of pronounced reallocation effects within many financial markets (Hassan et al., 2020; Pagano et al., 2020; Ramelli and Wagner, 2020).

In this paper, we empirically examine potential reallocation effects caused by COVID-19 by investigating the flow of venture capital (VC) investments around the world. VCs are an important class of financial intermediaries who raise capital mostly from institutional investors to fund early-stage entrepreneurial firms. These investment decisions can have a lasting impact on the aggregate productivity and job creation capacity of a country because the ability of many firms to innovate, operate, and grow depends on VC funding (Kortum and Lerner, 2000; Davila et al., 2003; Engel and Keilbach, 2007; Hirukawa and Ueda, 2008; Samila and Sorenson, 2010, 2011; Puri and Zarutskie, 2012; Bernstein et al., 2016).

As is well documented, VCs rapidly shift investments in existing portfolio companies and fund new ventures in response to market prospects and signals (Gompers and Lerner, 2004; Kaplan

[2] In January 2020, the GDP growth projection for advanced economies was +1.6%, while the projection released in June 2020 was -8%. Real GDP projections released by OECD were even worse.

and Strömberg, 2004; Gompers et al., 2008; Gompers et al., 2020a). Thus, it is not surprising that many analysts and commentators claimed at the time that "while traditional VC investment is expected to slow significantly over the next quarter, there are several niche segments of the market that could remain attractive to investors due to their applicability in the current environment" (KPMG, 2020).[3] Or, as argued by a study of EuropeanStartups.co,[4] while one third of the European VC-backed companies are strongly vulnerable to the pandemic crisis, for 20% of European tech-companies it represents a net benefit and an opportunity.

Hence, we study whether the onset of the COVID-19 pandemic led to reallocation effects within the global VC market by examining shifts in VC investment towards ventures directly or indirectly related to the spread of the virus. To estimate these effects, we construct a sample of VC funding deals that took place in 126 countries around the world between January 2018 and the end of July 2020. The sample uses data from Zephyr, a Bureau van Dijk database, which includes detailed information on VC investors, deal nature, firm raising capital, etc. An advantage of the database is that it provides a synopsis of the deal, which can be used to identify the scope, activity, and target customers/markets of the entrepreneurial venture. Using a textual analysis approach as in Fairclough (2003), we distinguish between pandemic-related and non-pandemic deals, where the former represents investments in firms that develop new technologies for addressing health issues and social needs that may arise in an era of global health pandemic and social distancing.

Our empirical strategy uses a difference-in-difference (DiD) approach that compares VC investments in pandemic-related and non-pandemic deals before and after the onset of the spread of COVID-19. Hence, we arrange our data in a panel format with time-series and cross-sectional dimensions. For the former, we adopt two-week periods as the temporal unit, for a total of 62 bi-monthly periods. For the latter, we follow two approaches to offer different granularity of analysis. First, at the global level, we aggregate all deals into pandemic-related and non-pandemic categories for each of the 62 temporal units. This approach assumes that VCs are global investors operating worldwide (Devigne et al., 2018). We approximate the onset of the spread of the COVID-19 virus using two alternatives: The first globally confirmed case in December 2019 and the declaration of

[3] Similarly, others stated that "Some shifts in VC investing will occur due to the economic displacement caused by COVID-19" towards "nascent technologies that are working on Covid and other related diseases" (Kruppa, 2020), or "communications software systems to tackle the pain points and hurdles that companies encountered when the majority of their workforce was working remotely" (Moore, 2020), or "logistics and delivery, edtech, and online entertainment…along with cyber security and data protection" (KPMG, 2020).
[4] https://europeanstartups.co/uploaded/2020/06/European-Startups-Launch-Report.pdf

a pandemic status made by the World Health Organization (WHO) in March 2020. Second, at the country level, for each time period we aggregate all deals into pandemic-related and non-pandemic categories using each country as the cross-sectional unit. This approach allows us to take into consideration the staggered nature of COVID-19 diffusion across countries, thus strengthening our identification strategy. In this case, VCs are still viewed as global investors, but we allow their investment choices to respond to the existence of confirmed COVID-19 cases in the country of the target company (alternatively for some of the analyses, in the country where the VC is based).

The results of our global analysis are consistent with a positive impact of the virus spread on pandemic-related sectors of the VC market. During the period after the initial early onset of the spread, VCs invest 39% more capital in such sectors. During the period following the declaration of a pandemic status by WHO, invested capital in pandemic-related deals increases by 78%. The number of deals also increases with the virus spread. The country-level analysis confirms the shift of VC investments towards pandemic-related transactions after the outbreak. Depending on the specification, we estimate that the invested amount increases by up to 44% and the number of deals by up to 5.8%. Thus, our analysis highlights the possibility of significant reallocation effects in the VC market driven by COVID-19.

In addition to the main effect, we establish several sources of heterogenous effects. First, exploring geographic differentials, we find that US and Chinese firms in pandemic-related sectors receive more capital concentrated within fewer deals, leading to a larger average amount per deal. We also show that US-based VCs increase invested capital in pandemic-related deals more than investors from the rest of world. Moreover, we document that the reallocation effects are stronger and more significant for experienced VCs. By contrast, transaction stage – early vs. late stage – and organizational form of the VC – independent VC (IVC) vs. corporate VC (CVC) – are not statistically significant drivers of heterogeneity, even though the magnitude of the estimated effect is slightly larger for late stage deals and independent VCs.

Last, we subject our estimations to several checks and robustness tests to ensure the validity of our empirical strategy and the inferences we draw from it. First, we verify the common trends assumption following Autor (2003). Second, we confirm the robustness of our results to alternative definitions and construction of the treatment measure, as well as approaches used to reduce the likelihood of false positives (non-pandemic deals erroneously considered to be pandemic-related) and false negatives (pandemic-related deals erroneously considered to be non-pandemic) in the operationalization of treatment. We also show that investments in deals related to social distancing also increase in the aftermath of the spread of COVID-19.

Our paper contributes to a rapidly growing literature that explores the reactions of investors and providers of capital to the spread of the pandemic and the effects on the post-COVID economy (Oldekop et al., 2020). These studies mostly focus on the banking system (Beck, 2020; Greenwald et al., 2020; Francis et al., 2020; Hoseini and Beck, 2020; Li et al., 2020, Dursun-de Neef and Schandlbauer, 2020) and the stock market (Alfaro et al., 2020; Baker et al., 2020a; Pagano et al., 2020; Ramelli and Wagner 2020), while the effects of COVID-19 on the VC market have remained relatively unexplored.

The VC market offers an ideal setting for exploring the potential reallocation effects of the spread of COVID-19. Unlike banks, VCs typically take equity stakes in young innovative firms in rapidly changing markets, and their ability to generate returns is related to how they can affect the future of sectors and markets by investing in ground-breaking ventures (Gompers, 1995; Gompers and Lerner, 2001; Da Rin et al. 2013). VCs can also implement quick decisions on their investment strategy due to streamlined managerial structures (Gompers et al., 2020a). Last, their investments are highly volatile and responsive to uncertainty and new opportunities arising from shock events (Gompers et al., 2008).

Thus, our paper adds to the literature that explores the temporal dynamics of VC investment around times of uncertainty and economic crises. Brown and Rocha (2020) and Howell et al. (2020) examine the pro-cyclicality of VC investments, including the immediate aftermath of the start of COVID-19, and highlight the sensitivity of early-stage VC investment to market conditions but do not explore possible reallocation effects. By contrast, Conti et al. (2019) show that in times of liquidity supply shocks, VCs tend to allocate funds to firms operating in their core sectors. The paper closest to ours is the recent work by Gompers et al. (2020b). By surveying over 1,000 VCs at more than 900 firms, they investigate how VCs change their investment strategy due to COVID-19 pandemic. While they find a slowdown in investment, they also document that approximately half of the respondents report a positive impact of the pandemic, thus highlighting the potential reallocation effects of the virus. We complement their survey-based results by implementing a comprehensive quantitative empirical analysis based on a large sample of actual VC transactions that take place around the world and cover a wide set of investors, sectors, and institutional factors.

We show that pandemic-related projects attract more investment on average in the aftermath of the virus spread and document substantial heterogenous effects underlying the aggregate patterns.

The rest of the paper is structured as follows. Section 2 describes the dataset and empirical strategy. Section 3 presents the main results of the analysis and some heterogenous effects. Section 4 provides robustness tests. Section 5 concludes.

## 2. Data and empirical strategy

### *2.1. Data structure and sources*

To estimate the reallocation effects of the diffusion of COVID-19 on the global VC market, we assemble a dataset that 1) includes detailed information at the VC transaction level to determine deal characteristics and 2) covers a period after the start of the spread of the new coronavirus as well as preceding periods to allow comparisons of the VC market before and after the outbreak of the COVID-19 pandemic.

To this end, we start with all VC deals that took place between January 2018 and July 2020 in 126 countries around the world available on Zephyr, a Bureau van Dijk database.[5] The database provides information on 1) characteristics of VC deals, such as invested amount, transaction date, and deal description; 2) VC investors, such as name and place of origin; and 3) companies raising capital, such as name, place of origin, and industry. The main advantage of the database is that it includes a deal synopsis. The synopsis can be used to identify deals involving ventures that develop technologies suited to tackle the needs of businesses and consumers in an environment of health pandemic and social-distancing (hereafter, we call such deals "pandemic-related"). To capture the spread of the virus by country, we obtain data from a public database "Daily confirmed COVID-19 cases", produced and updated by European Centre for Disease Prevention and Control (ECDC) and hosted by Our World in Data – a public data repository developed by the University of Oxford.[6] The database provides information on the diffusion of the disease by country, including the date of the first detected case of COVID-19.

[5] Using this time span, we can address the seasonality and cyclicality in VC investment by comparing any given post-COVID period to two pre-COVID periods during the previous two years. For instance, we can compare VC investment during March 2020 to that of March 2019 and March 2018. Given the cyclical nature of VC investment suggested by Cox et al. (2017) and Gompers et al. (2008), this approach should reduce possible biases that might arise through a comparison of pre- and post-COVID-19 periods.
[6] The database is available at https://ourworldindata.org/grapher/daily-cases-covid-19.

Our empirical strategy, discussed in detail in the next sub-section, follows a difference-in-differences approach. We compare VC investment flows in deals that involve ventures developing technologies related to the mitigation of contagious diseases like COVID-19 and social distancing problems to flows in deals unrelated to a pandemic environment, before and after the onset of the COVID-19 crisis. This requires the organization of the data in a panel structure with time-series and cross-sectional dimensions. As a temporal unit, we adopt 2-week periods, for a total of 62 bi-monthly periods. Our rationale is as follows: On the one hand, adopting a daily or even weekly frequency might lead to insufficient number of deals within a temporal unit and a few large deals could influence our results. On the other hand, we want to ensure that our treatment time-point is well defined. Adopting a monthly frequency would treat deals completed 30 days apart as part of the same temporal unit, which might not be appropriate given the speed of COVID-19 diffusion.[7]

For the cross-sectional dimension, we follow two approaches. First, at the global level, we aggregate all VC deals into two categories – pandemic-related and non-pandemic – for each of the 62 bi-monthly temporal units. We discuss these categories in detail in the next sub-section. Thus, in this “global dataset” we have two observations per temporal unit for a total of 124. This allows us to study the reallocation effects of COVID-19 under the assumption that VCs respond to a global signal for the outbreak of the pandemic. Our second approach focuses on the country level as the cross-sectional unit and we construct a “country dataset”. For each of the 126 countries in our database, we aggregate all deals for the 62 temporal units into two deal categories (pandemic-related and non-pandemic). This results in a total of 15,624 observations reflecting all possible time period-country-deal category combinations.[8] This dataset allows us to incorporate the staggered nature of the spread of COVID-19 across countries and implement a staggered DiD approach.

### *2.2. Treatment*

Our goal is to identify possible reallocation effects of the COVID-19 diffusion by exploring how VCs shift investment towards pandemic-related deals following the virus spread. Therefore, we need to determine 1) pandemic-related deals and 2) post-diffusion periods for each country.

[7] The 2-week period also better approximates the length of development of COVID-19 symptoms (and, therefore, case identification) that the virus generally shows after the beginning of contagion, i.e. 14 days (Lauer et al., 2020).
[8] We note that when we aggregate the data by VC investor, the number of countries decreases to 112, due to missing information on the country of origin for some VCs, resulting in a total of 13,888 observations.

In our main analysis, we categorize as pandemic-related deals that are strictly associated with the health value-chain and in the fields of biology, chemistry, healthcare, and pharmaceutical development. To determine if a deal should be assigned to the pandemic-related category, we use an "Information Extraction from Text" method (Jiang, 2012). The method analyzes unstructured text to collect information and provide structured informative output. Following this approach, we analyze 3 textual fields of the sample deals, namely: deal editorial, comments, and rationale. Deal editorial and comments are provided by Zephyr analysts and describe the main features of the deal, including information about target firm and its projects (Reiter, 2013). Deal rationale is generally sourced from press releases or communication produced by the firm (Florio et al., 2018). We assign a deal to the pandemic-related category if at least one of the textual fields mentions at least one word from a list of predetermined keywords. The list consists of 5 groups of words related to "biology", "chemistry and pharmaceuticals", "health", "healthcare supply chain", and "medical science".[9] We create a dummy variable, *Pandemic*, which takes the value of 1 if the deal textual fields mention at least one key word, and 0 otherwise. To not undermine our DiD strategy, we use words that can be found in the deal synopses even before the novel coronavirus was isolated by the Chinese Centre for Disease Control and Prevention in January 2020 under the provisional name 2019-nCoV. Therefore, we exclude words commonly used to designate the current pandemic, such as novel or new coronavirus, 2019-nCoV, COVID, COVID-19, SARS, and SARS-CoV-2.

An alternative approach to identify pandemic-related deals might be to classify sectors as pandemic-related based on technological characteristics that make them more sensitive to a health pandemic (or social distancing), and then use the sector of a target firm – usually identified through NACE codes[10] – to establish if a deal is pandemic-related.[11] However, in our context this way of

[9] Table A.1 in the Appendix provides the list of all keywords related to these fields. To implement the textual analysis, we adopt the following process. First, we perform preliminary data-cleaning procedures to increase the probability of determining the right category (Allahyari et al., 2017). Specifically, we delete punctuation and extra spaces and transform all letters into lowercase (for instance, "Health-care" is converted to "healthcare"). Second, we ensure that the available text does not contain obvious typos. We replace misspelled words with the correct ones (for instance, "healht" is converted to "health"). Third, we reconduct words belonging to the same etymological family to a single root by implementing a stemming approach (Porter, 1980). For instance, based on this methodology, we would reduce plurals to singular terms (e.g. "hospitals" to "hospital") and nouns to adjectives (e.g. "therapy" to "therapeutic") when related to the common concept.

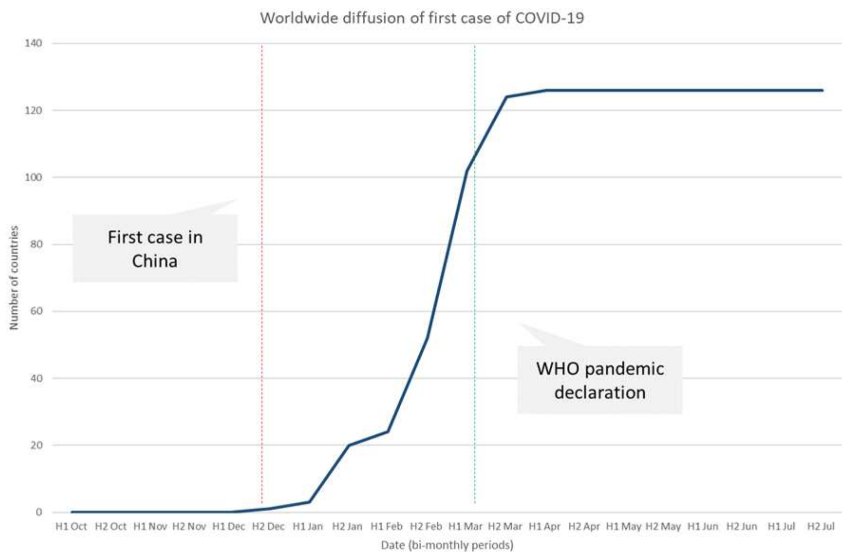
[10] European Commission (2008). NACE Rev. 2. Statistical classification of economic activities in the European Community. *Eurostat Methodologies and Working Papers*, Office for Official Publications of European Communities, ISBN 978-92-79-04741-1, https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

[11] The approach is followed by Dingel and Neiman (2020) who consider the extent to which a job in a given industry can be performed at home during a lockdown, and Koren and Pető (2020) who measure how much businesses rely on close social proximity.

categorizing a sector based on the average characteristics of firms belonging to it does not take into account intra-sector heterogeneity of entrepreneurial ventures and can lead to measurement errors. On the one hand, projects related to a health pandemic may be developed by firms operating in sectors other than healthcare. On the other, some projects launched by firms in the healthcare sector might clearly be non-pandemic.[12]

Our analysis compares deals in pandemic-related and non-pandemic categories before and after the onset of the spread of COVID-19. Identification of post-treatment periods is based on the date of the first officially confirmed case of COVID-19 as a proxy for the beginning of the spread of the pandemic in a country. Figure 1 provides a snapshot of the global evolution of the pandemic by showing over time the number of countries that have experienced a COVID-19 case.

**Figure 1 Diffusion of (First Cases) COVID-19 at the Global Level**




The first confirmed case emerged in China on December 31, 2019, even though according to the media, Chinese authorities had identified cases of the virus weeks earlier.[13] In the following

[12] In Table A.2 of the Appendix, we provide several examples drawn from our sample. We show in Figure A.1 that all main NACE macro-sectors include companies that develop pandemic-related technologies. In un-tabulated checks based on finer categorizations of sectors, we also find that such firms are present in 62% (30%) of all 2-digit (4-digit) NACE sectors.

[13] https://www.theguardian.com/world/2020/mar/13/first-covid-19-case-happened-in-november-china-government-records-show-report.

months, by mid-March 2020 when WHO officially declared pandemic status, most of the countries around the world (about 80%) had faced the disease.[14] For the remaining 20%, the first COVID-19 case emerged during the first two weeks of April 2020. The time-series pattern suggests that while the diffusion of COVID-19 was relatively quick, there is a degree of variability in its spread across countries. Hence, given that our temporal unit of analysis is a 2-week period, we construct a dummy variable, *First Case G*(lobal), which takes the value of 1 for deals occurring after the second half of December 2019, and 0 otherwise. While this approach captures the earliest signal for the (potentially) global pandemic, it is possible that VC investors could not fully anticipate the magnitude of the upcoming crisis. As a result, we might underestimate reallocation effects. Hence, we construct another dummy variable, *WHO*, which takes the value of 1 for deals occurring after the second half of March 2020 when the WHO declared a global pandemic status. We note that, as mentioned, by that time most countries have already experienced COVID-19 cases. Therefore, to implement our preferred empirical approach at the country level, we construct a dummy variable *First Case C*(ountry), which takes the value of 1 for deals funded after the 2-weeks period in which the first COVID-19 case for the specific country was confirmed.

### *2.3. Dependent variables*

We focus on two outcome variables. The first is invested amount. We aggregate the total amount of capital invested by VCs in two deal categories – pandemic-related and non-pandemic – during each period and take a logarithmic transformation in the analysis. The second measure is the (log of) number of VC transactions. This variable accounts for how many deals are completed in the two categories during each period. The analysis of both amount and number of deals allows us to shed more light on VCs' investments behavior. For instance, if an increase in the amount is not matched by a corresponding increase in number of deals, we could infer that investors pursue smaller number of deals, but with a larger average size. Unless otherwise specified, the dependent variables are aggregated at the level of the country of the target company.

Figure A.2 in the Appendix reports total number of deals and invested amounts by quarter from Q1 2018 to Q2 2020 reported in the Zephyr database. The figures are similar in magnitude

[14] https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

and time-series patterns to those reported in Pitchbook.[15] This suggests that our analysis is based on a representative sample with comprehensive worldwide coverage. Similarly, Figure A.3 shows the average bi-monthly number of VC transactions over periods before and after the pandemic onset for the world market, as well as the US, China, and the European Union. We note that US figures follow a similar path to the one reported by Howell et al. (2020) based on CB Insights data.

### 2.4. *Econometric strategy*

To identify the reallocation effects on VC investment created by the spread of COVID-19, we rely on variations of a difference-in-differences methodology. The approach is extensively used in evaluation studies to examine whether an exogenous event (*Treatment*) has a causal effect on a given outcome of interest. In particular, the method compares changes in the outcome for a group of units subject to the event (*Treated*) and another group of units similar in all aspects except for not being subject to the event (*Control*), for a period of time before and after the event. In our context, we compare VC investments in pandemic-related (*Treated*) and non-pandemic (*Control*) categories before and after the onset of the spread of COVID-19.[16]

Depending on the cross-sectional unit of analysis, we perform two sets of estimations at a global and country level, respectively. For the first set, we consider the overall global market as the unit of analysis. For the second set, which is our preferred approach, we rely on the staggered nature of treatment due to the country-specific diffusion of COVID-19. Hence, the first model we estimate is specified as follows:

$$Y_{dt} = \alpha Pandemic_d + \beta First\ Case\ G_t + \gamma Pandemic_d \times First\ Case\ G_t + \mu_d + \tau_t + \\ + \lambda Trend_{dt} + \epsilon_{dt} \quad (1)$$

where *t* denotes a bi-monthly period and *d* denotes deal category (pandemic-related or not). *Y* is one of the outcome variables. *Pandemic*, which takes the value of 1 for pandemic-related deals and 0 for the non-pandemic ones, controls for unobserved heterogeneity across deal categories, while *First Case G* controls for common shocks to both deal categories in the aftermath of the first

[15] See https://assets.kpmg/content/dam/kpmg/xx/pdf/2020/07/venture-pulse-q2-2020-global.pdf.

[16] Table A.3 in the Appendix reports t-tests of the differences in the means of the outcome variables for pandemic-related and non-pandemic deals.

COVID-19 case globally. In some specifications we use the indicator *WHO* as an alternative to *First Case G* to capture post-treatment period. We include deal category fixed effects, $\mu_d$ to account for unobserved time-invariant heterogeneity across deal categories. We add time fixed effects $\tau_t$ to control for common shocks at time *t*. We also control for temporal patterns independent of the diffusion of COVID-19 by adding a set of linear trends for each deal category ($Trend_{dt}$). Last, $\epsilon_{dt}$ is the error term.

Our second set of analysis explores the staggered spread of the COVID-19 pandemic across countries.[17] In this case, the model is specified as follows:

$$Y_{dit} = \alpha Pandemic_d + \beta First\ Case\ C_{it} + \gamma Pandemic_d \times First\ Case\ C_{it} + \mu_{di} + \tau_t \ + \\ + \lambda Trend_{dit} + \epsilon_{dit} \tag{2}$$

where *i* denotes a country and *t* and *d* denote time period and deal category, respectively. *First Case C* has a staggered nature and controls for common shocks to all deals in a given country after the spread of COVID-19 in that country. We control for unobserved heterogeneity across the units of analysis by including country-deal category fixed effect, $\mu_{di}$, along with time fixed effects to account for common shocks at time *t*, $\tau_t$. We also account for possible country-deal category trends through ($Trend_{dit}$) and cluster the errors, $\epsilon_{dit}$, at the country level.[18]

In both specifications, the coefficient $\gamma$ represents the DiD estimate of reallocation effects of COVID-19 on the VC market. Support for the reallocation argument requires a positive and statistically significant point estimate, which would indicate an increase in VC investment towards pandemic-related projects after the spread of COVID-19.

### *2.5. Preliminary evidence*

We first offer preliminary, mostly descriptive, analysis of the dynamics of VC investments in the two categories of deals – pandemic-related and non-pandemic – before and after the outbreak of COVID-19.

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[17] Similar DiD estimation in country-by-sector setting is often used in research on financial and economic development (e.g., Braun and Larrain, 2005; Levchenko et al., 2009; Desbordes and Wei, 2017; Beck et al., 2018).

[18] We have also estimated equation (2) using standard errors clustered at the country deal-category level. The estimates are reported in Table A.4 of the Appendix. We note that our results are robust to this alternative approach.

### Table 1 Evolution of VC Investments

#### Panel A Total Amount

| | Before | | | After | | | Growth rate | | | Difference |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | Pandemic-related | Non-pandemic | Total | Pandemic-related | Non-pandemic | Total | Pandemic-related | Non-pandemic | |
| US | 6.259 | 0.723 | 5.535 | 7.670 | 1.127 | 6.543 | 23% | 56% | 18% | 38% |
| China | 2.343 | 0.299 | 2.044 | 1.555 | 0.402 | 1.153 | -34% | 34% | -44% | 78% |
| EU | 0.798 | 0.138 | 0.660 | 0.646 | 0.121 | 0.525 | -19% | -12% | -20% | 9% |
| World | 10.924 | 1.384 | 9.540 | 12.169 | 1.853 | 10.316 | 11% | 34% | 8% | 26% |

#### Panel B Number of Deals

| | Before | | | After | | | Growth rate | | | Difference |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | Pandemic-related | Non-pandemic | Total | Pandemic-related | Non-pandemic | Total | Pandemic-related | Non-pandemic | |
| US | 624 | 54 | 570 | 558 | 51 | 507 | -11% | -5% | -11% | 6% |
| China | 48 | 8 | 39 | 42 | 9 | 33 | -12% | 11% | -17% | 28% |
| EU | 79 | 10 | 68 | 71 | 12 | 59 | -10% | 11% | -14% | 24% |
| World | 883 | 86 | 797 | 831 | 90 | 741 | -6% | 4% | -7% | 11% |

#### Panel C Median Amount

| | Before | | | After | | | Growth rate | | | Difference |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | Pandemic-related | Non-pandemic | Total | Pandemic-related | Non-pandemic | Total | Pandemic-related | Non-pandemic | |
| US | 2.016 | 2.879 | 1.943 | 2.434 | 3.821 | 2.307 | 21% | 33% | 19% | 14% |
| China | 6.574 | 12.554 | 6.368 | 10.440 | 13.038 | 6.544 | 59% | 4% | 3% | 1% |
| EU | 2.000 | 3.282 | 2.000 | 2.207 | 4.175 | 2.011 | 10% | 27% | 1% | 27% |
| World | 2.004 | 3.458 | 1.914 | 2.274 | 4.407 | 2.164 | 13% | 27% | 13% | 14% |

**Note**: Panel A shows average total amount (€ billion) of VC investment per bi-monthly period during the pre-treatment (01/01/2018-12/15/2019 for China and World; 01/01/2018-15/01/2020 for US and EU) and post-treatment timeframe (12/16/2019-07/31/2020 for China and World; 01/16/2020-07/31/2020 for US and EU). Panel B shows average number of deals per bi-monthly period during the same timeframe, while Panel C shows median amount (€ million) of investment. The column "Growth Rate" reports the growth rate from the pre-treatment to the post-treatment figure across each deal category. The column "Difference" reports the difference between "Growth Rate" of pandemic-related and non-pandemic deals.

Panel A of Table 1 shows the amount of investment in pandemic-related and non-pandemic deals before and after the outbreak globally and in three geographic areas: United States, China, and European Union. Note that the pre- and post-treatment horizons cover a different number of bi-monthly periods. Hence, we first compute the total invested amount for each bi-monthly period and then take the average across all periods before the onset of the pandemic and afterwards. Globally, VC investments increase from 10.92 to 12.17 billion € per period, which corresponds to a growth rate of about 11%. The increase is driven by deals involving US firms because the average investment amount per period in China and EU drops by 34% and 19%, respectively. More importantly, investments in pandemic-related and non-pandemic deals change at different rates. At the global level, investment in pandemic-related deals goes up by 34%, while investment in non-pandemic ones increases by only 8%. This leads to a DiD estimate of 26%.

We observe consistent patterns in the three major geographic areas. In US, investments in pandemic-related deals increase by 56%, compared to 18% in non-pandemic ones, which results in a DiD estimate of 38%. In China, the trends between the two deal categories are even divergent: investment in pandemic-related deals increases by 34%, while investment in non-pandemic ones decreases by 44%, for a DiD estimate of 78%. Last, investments within EU decrease for both categories, but to a lesser extent for pandemic-related (-12%) than non-pandemic (-20%) deals. As a result, the DiD estimate is positive, as shown in the last column of Panel A.

In Panel B we present similar analysis using number of deals. The average number of deals per bi-monthly period decreases by 6% at a global level, as well as in each of the three geographic areas, with changes ranging from -10% to -12%. The world-level total change appears to be driven by a reduction of 7% in the average number of non-pandemic deals. By contrast, average number of pandemic-related deals per period increases globally by 4%. Importantly, the DiD estimate indicates a relative increase in the average number of pandemic-related deals of 11%. Across all segments, the DiD estimate is positive and ranges from 6% in the US to 28% in China.

Last, in Panel C we report median investment amount per period before and after the onset of the pandemic. Similar to the results in Panel A, the world-level median investment amount after the outbreak increases in both deal categories, but more so for pandemic-related deals. The same pattern is detected in each of the three geographic areas. Overall, the analysis suggests the average size of pandemic-related deals increases in the aftermath of the onset of the COVID-19 crisis.

## 3. Results

### *3.1. Global analysis*

We estimate the model outlined in equation (1) using the global dataset and report results in Table 2. In columns (1) and (2) we focus on the amount of capital invested in pandemic-related deals. The coefficient on the interaction term *Pandemic* × *First Case G* is positive and marginally significant at the 10% level. While the estimate implies an increase in invested amount of about 39%, as previously argued it might underestimate the reallocation effect of COVID-19. Therefore, in column (2) we use the *WHO* indicator. The estimate of the interaction term *Pandemic* × *WHO* is positive and statistically significant at the 1% level. The point estimate doubles and implies an increase in amount of invested capital in pandemic-related deals of about 78% during the post-treatment period. In columns (3) and (4) we examine the reallocation effect in terms of number of VC transactions and obtain consistent results. The global spread of COVID-19 is associated with a significant increase in the number of pandemic-related deals, especially when the post-treatment period is captured through the declaration of pandemic status by the WHO.

**Table 2 Global Flows of VC Investment**

| | VC invested amount | | Number VC transactions | |
|---|---|---|---|---|
| Dependent Variable | (1) | (2) | (3) | (4) |
| *Pandemic* × *First Case G* | 0.388* | | 0.048 | |
| | (0.211) | | (0.065) | |
| *Pandemic* × *WHO* | | 0.778*** | | 0.186*** |
| | | (0.194) | | (0.061) |
| Observations | 124 | 124 | 124 | 124 |
| Adjusted R-squared | 0.896 | 0.913 | 0.991 | 0.992 |
| Deal Category Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Deal Category Trend | Yes | Yes | Yes | Yes |

**Note**: The analysis covers 62 bi-monthly periods from 01/01/2018 to 07/31/2020. *Pandemic* is an indicator that takes the value of 1 for deals that belong to the pandemic-related category, and 0 otherwise. *First Case G* is an indicator that takes the value of 1 for periods after the beginning of the global spread of COVID-19 (12/31/2019), i.e. after the first confirmed case worldwide, and 0 otherwise. *WHO* is an indicator that takes the value of 1 for periods after the declaration of pandemic by the WHO (03/12/2020), and 0 otherwise. The table reports coefficient estimates followed by standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Overall, the global analysis highlights a shift towards pandemic-related investments in the VC market in the periods following the outbreak of the COVID-19 virus. In addition to that, the analysis, and the resultant variation in the estimates of the effect obtained from the two methods used to capture post-treatment periods, underscores the importance of the country-level approach that makes use of the staggered nature of the spread of the virus and strengthens the identification.

### *3.2. Country-level analysis*

We now turn to the country-level analysis by estimating the staggered version of our model, namely equation (2). The cross-sectional unit is country and the temporal unit is again bi-monthly time period. For each dependent variable, in addition to the control variables and fixed effects, we estimate one specification with a linear trend at the country-deal category level and one without.[1]

The estimation results are presented in Table 3. In column (1) we estimate that the diffusion of COVID-19 is associated with an increase in the amount invested in pandemic-related deals of .272 and the estimate is significant at the 5% level. In column (2) we augment the specification of column (1) with country-deal category linear trends. When we include these trends, the magnitude of the effect increases to .438 and becomes statistically significant at the 1% level. Thus, in the period after the start of the spread of COVID-19, the invested amount in pandemic-related deals increases by about 44%.

In columns (3) and (4), we use as a dependent variable the (log of) number of deals. In both cases we document a positive effect of the diffusion of COVID-19 on the number of pandemic-related deals between 5% and 5.8% and the estimates are statistically significant at the 1% level. Thus, the country-level analysis confirms a shift of VC investment towards pandemic-related deals following the outbreak of COVID-19, consistent with the argument that the pandemic leads to the reallocation of financial resources in the economy.

[1] Our sample covers the time span between January 2018 and July 2020. However, since in this case the pre-treatment period is longer than post-treatment period, for robustness we also estimate the regressions restricting the time span to 2019 and 2020 only. The results are qualitatively similar to those obtained with the whole sample and are available upon request.

**Table 3 Baseline Results – Country-level Analysis**

| | VC invested amount | | Number VC transactions | |
|---|---|---|---|---|
| Dependent Variable | (1) | (2) | (3) | (4) |
| *Pandemic × First Case C* | 0.272** | 0.438*** | 0.050*** | 0.058*** |
| | (0.112) | (0.140) | (0.018) | (0.018) |
| Observations | 15,624 | 15,624 | 15,624 | 15,624 |
| Adjusted R-squared | 0.669 | 0.661 | 0.857 | 0.859 |
| Country-Deal Category Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Country-Deal Category Trend | No | Yes | Yes | Yes |

**Note**: The analysis covers 62 bi-monthly periods from 01/01/2018 to 07/31/2020 and 126 countries. *Pandemic* is an indicator that takes the value of 1 for deals that belong to the pandemic-related category, and 0 otherwise. *First Case C* is an indicator that takes the value of 1 for periods after the beginning of the spread of COVID-19 in country *c*, i.e. after the first confirmed case of COVID-19 in the country, and 0 otherwise. The table reports coefficient estimates followed by standard errors, clustered at country level, in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

### *3.3. Heterogeneous effects*

Having established the average impact of the COVID-19 diffusion, we proceed to examine possible heterogenous effects. We explore how the reallocation effects of the pandemic might vary with deal and investor characteristics. Specifically, we focus on geographic effects, experience of the VC, investment stage, and organizational structure.

*Geographic area*

First, we explore possible heterogeneous effects related to the two markets with the largest concentration of VC investors and entrepreneurial ventures, namely: US and China. To this end, we construct two indicators: *US (CN)* takes the value of 1 for deals where the funded firm is in the US (China), and 0 otherwise. We then interact these two indicators with the treatment variable and estimate the following model:

$$Y_{dit} = \alpha Pandemic_d + \beta First\ Case\ C_{it} + \gamma_1 Pandemic_d \times First\ Case\ C_{it} + \ \gamma_2 Pandemic_d \times First\ Case\ C_{it} \times US_{it} + \ + \gamma_3 Pandemic_d \times First\ Case\ C_{it} \times\ CN_{it} + \mu_i + \tau_t\ + \lambda Trend_{dit} + \epsilon_{dit} \tag{3}$$

where, $\gamma_2$ and $\gamma_3$ capture the differential impact for deals involving firms based in the US and China, respectively. By contrast, $\gamma_1$ captures the average effect for companies based anywhere else. The results of this estimation are shown in columns (1) and (3) of Table 4, Panel A. First, we note that $\gamma_1$ is positive and statistically significant at the 1% level in both specifications. Thus, the overall impact of COVID-19 is confirmed even after excluding the two markets from the analysis. Moreover, column (1) suggests that the positive effect on the invested amount is stronger for deals in these two markets. The coefficients on the triple interaction terms *Pandemic* × *First Case C* × *US* and *Pandemic* × *First Case C* × *CN* are positive and significant at the 5% and 1% levels, respectively. The overall effects for deals involving firms located in the US and China are captured by the linear combinations of (A) + (B) and (A) + (C), respectively. Note that both are positive and significant at the 1% level in column (1).

In column (3) we explore the effect of COVID-19 on number of deals. The coefficients on the triple interaction terms *Pandemic* × *First Case C* × *US* and *Pandemic* × *First Case C* × *CN* are negative this time and significant at the 1% and 5% levels, respectively. This suggests that VC investors incrementally fund fewer pandemic-related deals in these two markets. By looking at the linear combination terms, we estimate a significant negative overall effect (-.106) for transactions involving US-based firms and an insignificant effect of .026 for Chinese targets. This suggests that in the US, the average size of pandemic-related deals funded after the outbreak increased.

## Table 4 Heterogeneous Effects

### Panel A Geography

| Dependent Variable | | VC invested amount (1) | (2) | Number VC transactions (3) | (4) |
|---|---|---|---|---|---|
| *Pandemic × First Case C* | (A) | 0.432*** | 0.472*** | 0.060*** | 0.064*** |
| | | (0.141) | (0.148) | (0.018) | (0.017) |
| *Pandemic × First Case C × US* | (B) | 0.280** | | -0.166*** | |
| | | (0.113) | | (0.015) | |
| *Pandemic × First Case C × CN* | (C) | 0.441*** | | -0.034** | |
| | | (0.130) | | (0.017) | |
| *Pandemic × First Case C × VC US* | (D) | | 0.206 | | -0.099*** |
| | | | (0.135) | | (0.017) |
| *Pandemic × First Case C × VC CN* | (E) | | 0.259* | | -0.035* |
| | | | (0.147) | | (0.018) |
| Linear combination (A) + (B) | | 0.713*** | | -0.106*** | |
| Linear combination (A) + (C) | | 0.874*** | | 0.026 | |
| Linear combination (A) + (D) | | | 0.678*** | | -0.035 |
| Linear combination (A) + (E) | | | 0.731*** | | 0.029 |
| Observations | | 15,624 | 15,624 | 15,624 | 15,624 |
| Adjusted R-squared | | 0.669 | 0.661 | 0.857 | 0.859 |
| Country-Deal Category Fixed Effects | | Yes | Yes | Yes | Yes |
| Time Fixed Effects | | Yes | Yes | Yes | Yes |
| Country-Deal Category Trend | | Yes | Yes | Yes | Yes |

**Note**: The analysis covers 62 bi-monthly periods from 01/01/2018 to 07/31/2020 and 126 countries. *Pandemic* is an indicator that takes the value of 1 for deals that belong to the pandemic-related category, and 0 otherwise. *First Case C* is an indicator that takes the value of 1 for periods after the beginning of the spread of COVID-19 in country *c*, i.e. after the first confirmed case of COVID-19 in the country, and 0 otherwise. The linear combinations of coefficients represent the point estimates, and their statistical significance, of the treatment effect on outcome variables (invested amount and number of transactions) for deals involving US (A+B) or Chinese (A+C) firms or completed by US (A+D) or Chinese (A+E) VCs, respectively. The table reports coefficient estimates followed by standard errors, clustered at country level, in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Panel B Investor Experience, Investment Stage, and VC Type**

| | | VC invested amount | | | Number VC transactions | | |
|---|---|---|---|---|---|---|---|
| Dependent Variable | | (1) | (2) | (3) | (4) | (5) | (6) |
| *Pandemic × First Case C* | (A) | 0.308*** | 0.291*** | 0.288*** | 0.037*** | 0.030** | 0.038*** |
| | | (0.085) | (0.091) | (0.100) | (0.012) | (0.011) | (0.011) |
| *Pandemic × First Case C × Young VC* | (B) | -0.144** | | | -0.017** | | |
| | | (0.073) | | | (0.007) | | |
| *Pandemic × First Case C × Later Stage* | (C) | | 0.063 | | | 0.005 | |
| | | | (0.079) | | | (0.009) | |
| *Pandemic × First Case C × CVC* | (D) | | | -0.101 | | | -0.008 |
| | | | | (0.117) | | | (0.013) |
| Linear combination (A) + (B) | | 0.164* | | | 0.019 | | |
| Linear combination (A) + (C) | | | 0.355*** | | | 0.035*** | |
| Linear combination (A) + (D) | | | | 0.187* | | | 0.030** |
| Observations | | 31,248 | 31,248 | 31,248 | 31,248 | 31,248 | 31,248 |
| Adjusted R-squared | | 0.577 | 0.616 | 0.628 | 0.732 | 0.790 | 0.842 |
| Country-Deal Category Fixed Effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Country-Deal Category Trend | | Yes | Yes | Yes | Yes | Yes | Yes |

**Note**: The analysis covers 62 bi-monthly periods from 01/01/2018 to 07/31/2020 and 126 countries. *Pandemic* is an indicator that takes the value of 1 for deals that belong to the pandemic-related category, and 0 otherwise. *First Case C* is an indicator that takes the value of 1 for periods after the beginning of the spread of COVID-19 in country *c*, i.e. after the first confirmed case of COVID-19 in the country, and 0 otherwise. *Young VC* is an indicator that takes the value of 1 for VCs in the bottom quartile of the age distribution of VC firms, and 0 otherwise. *Later Stage* is an indicator that takes the value of 1 for deals that are later stage investments, and 0 for early stage investments. *CVC* is an indicator that takes the value of 1 for Corporate VCs, and 0 for Independent VCs. The linear combinations of coefficients represent the point estimates, and their statistical significance, of the treatment effect on outcome variables (invested amount and number of transactions) for deals involving younger VCs (A+B), later rounds of investment (A+C), or completed by corporate VCs (A+D), respectively. The table reports coefficient estimates followed by standard errors, clustered at country level, in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

As a second source of heterogeneity, we explore whether the investment decisions of US and Chinese VCs in the aftermath of the pandemic differ from those of VCs in other countries. For this analysis, the dependent variables are computed at the country of origin of the VC (for example, we use total amount of capital invested in pandemic-related deals during each period by VCs based in country *i*). We estimate equation (3) but for this analysis *US* and *CN* are indicators for deals with US and Chinse investors, respectively. For expositional purposes we rename the variables *VC US* and *VC CN*.

The estimation results are shown in columns (2) and (4) of Table 4, Panel A. We find that the estimates of the main effect are positive and significant at the 1% level in both specifications. In terms of invested amounts, the behavior of US-based VCs is similar to that of all others as the interaction term *Pandemic* × *First Case C* × *VC US* in column (2) is not significant. By contrast, the positive and significant interaction term *Pandemic* × *First Case C* × *VC CN* of .259 suggests that Chinese VCs tend to invest more in pandemic-related deals relative to all others. The linear combination estimates in column (2) suggest that the overall effect of the onset of the COVID-19 spread on VC invested amount is positive and significant. In terms of number of deals, we note from the linear combination estimates in column (4) that US and Chinese VCs neither increase nor decrease their number of funded pandemic-related deals even though the coefficients on the triple interaction terms of -.099 and -.035 are significant, which suggests that they invest differently from other VCs.

*Investor experience*

Extant literature suggests that VC funding might be driven by factors such as overreaction to perceived investment opportunities or changes in fundamentals of target firms or sectors (Gupta, 2000; Gompers and Lerner, 2004). Along this line, Gompers et al. (2008) examine determinants and success of investments by VCs with different levels of experience and specialization when market opportunities change and find greater investment response by VCs with more experience. Hence, we investigate whether VC experience magnifies or attenuates the reallocation effects. We construct a dummy variable, *Young VC*, which takes the value of 1 for deals where the VC is in the bottom quartile of the age distribution for all VC investors in our sample, and estimate the following model:

$$Y_{dit} = \alpha Pandemic_d + \beta First\ Case\ C_{it} + \gamma_1 Pandemic_d \times First\ Case\ C_{it} + \gamma_2 Pandemic_d \times First\ Case\ C_{it} \times Young\ VC_{it} + \mu_i + \tau_t + \lambda Trend_{dit} + \epsilon_{dit} \quad (4)$$

where $Y_{dit}$ is measured at the country of origin of the VC, $\gamma_1$ captures the reallocation effect for more experienced investors, while $\gamma_1 + \gamma_2$ the reallocation effect for less experienced VCs. The estimation results are reported in columns (1) and (4) of Table 4, Panel B. We find that more experienced investors significantly increase investment amount as the coefficient of the interaction term *Pandemic* × *First Case C* in column (1) is positive (.308) and statistically significant at the

1% level. The effect is reduced for less experienced VCs based on the negative and significant coefficient of the triple interaction term in column (1). In fact, the spread of the virus appears to have smaller effect on the investment decisions, in terms of amount, of younger VCs. Nevertheless, the linear combination term in column (1) is positive and significant, albeit at the 10% level only. Thus, even younger VCs increase investment in pandemic-related deals.

In terms of number of deals, the estimates in column (4) suggest more experienced VCs increase investment in pandemic-related deals. The coefficient of the interaction *Pandemic* × *First Case C* is positive and statistically significant at the 1% level. The differential effect estimated for less experienced VCs negative (-.017) and significant at the 5% level, which implies that younger VCs invest substantially less than their more experienced counterparts. In fact, the insignificant linear combination estimate in column (4) indicates that, in terms of number of deals, the COVID-19 outbreak has not discernable effect for young VCs. In line with Gompers et al. (2008) and Sorensen (2007), we infer that the COVID-related reallocation in the VC market is concentrated within the group of more experienced investors who seem more responsive to signals of investment opportunities.

*Investment round*

We further investigate possible heterogenous effects related to the stage of financing by distinguishing between early and late investment rounds. During recessions the greater uncertainty created by the economic slowdown can lead VCs to a more cautious investment approach. This, in turn, could affect the funding of early-stage deals or VCs specializing in early-stage transactions to a greater extent (Kaplan and Schoar, 2005; Gompers et al., 2008; Townsend, 2015; Howell et al., 2020). Along these lines, practitioners suggest that VCs will respond to the COVID-19 health crisis by giving priority to ventures in later investment rounds, while overlooking new investments (Mason, 2020). This is consistent with the trends in number of VC deals and new investments in the US in the second quarter of 2020 observed by Gompers et al. (2020b) and Howell et al. (2020).

To the extent that late-stage investments are more resilient to negative shocks, one could expect that in the initial months of the pandemic the reallocation effects manifest more clearly for late-round deals than for early stage ones. By contrast, it could be that early stage VC investments, which are more sensitive to recessions, switch faster away from negatively affected sectors by the COVID-19 crisis.

To analyze the differential reallocation effect for early and late investments, we construct a dummy variable, *Later Stage*, which takes the value of 1 for later-stage deals, and 0 for early-stage ones. We consider seed stage, as well as the 1st and 2nd investment rounds as early-stage. By contrast, we categorize as later stage all stages from the 3rd to 8th rounds. We then estimate equation (4) replacing *Pandemic* × *First Case C* × *Young VC* with *Pandemic* × *First Case C* × *Later Stage*.

The estimation results are shown in columns (2) and (5) of Table 4, Panel B. The coefficient of *Pandemic* × *First Case C* in column (2) is significant, which suggests that the diffusion of the pandemic positively affects invested amounts in pandemic-related deals that are early-stage. We do not find a significant difference in the estimated effects for the early-stage and late-stage deals as the coefficient of the triple interaction *Pandemic* × *First Case C* × *Later Stage* is not statistically significant. The linear combination estimate in column (2) confirms that the pandemic leads to an increase in invested amount in pandemic-related deals at early stages as well, but the reallocation effect is slightly lower in magnitude and statistically less significant. In column (5) we explore the differential effect of investment stage on number of pandemic-related deals and conclude that our insights are consistent with those observed in column (2).

*Type of investor*

We also analyze possible heterogenous effects created by type of investor. Specifically, we distinguish between IVC and CVC. The uncertainty associated with the diffusion of COVID-19 may induce different responses by these VC types given their different organization, incentives, mode of operation, investment objectives, and constraints. On the one hand, IVCs aim at increasing the value of portfolio companies prior to exit (Gompers and Lerner, 2001). However, the increased uncertainty following the pandemic onset may induce VCs to delay funding due to worsening market conditions and, consequently, performance of VC-backed firms. On the other hand, CVCs are more likely to invest in companies that develop technologies complementary to those of the CVC parent (Dushnitsky and Lenox, 2006; Da Rin et al., 2013; Maula et al., 2013) or that can lead to strategic partnerships (Gompers and Lerner, 2000). CVCs may also postpone investment or partnerships waiting for emerging technological discontinuities. The differences between IVCs and CVCs underscore the need to examine possible differential behavior of these two types of investors. Hence, we create a dummy variable, *CVC*, that takes the value of 1 for deals involving a corporate VC, and 0 for independent VC. We then estimate equation (4) after replacing the term *Pandemic* × *First Case C* × *Young VC* with the term *Pandemic* × *First Case C* × *CVC*.

The estimation results are in columns (3) and (6) of Table 4, Panel B. The analysis suggests that IVCs increase investment in pandemic-related deals along both outcome dimensions: amount and number of deals. The point estimate of the coefficient of *Pandemic* × *First Case C* is positive and significant at the 1% level in columns (3) and (6). However, corporate VCs do not respond in a systematically different manner as indicated by the insignificant estimates of the coefficient on the triple interaction *Pandemic* × *First Case C* × *CVC*. Hence, in line with the survey evidence reported by Gompers et al. (2020b), we conclude that while relevant, investor type is not a primary determinant of the reallocation effect in the VC market.

## 4. Robustness tests

In this section, we conduct several tests to verify the robustness of our insights about the reallocation effects of COVID-19. The first test is related to the methodology behind our empirical strategy. We examine the common trends assumption following Autor (2003). We then conduct a set of tests about: (*i*) robustness of our definition of treated group; (*ii*) alternative operationalization of the dependent variable; (*iii*) the placebo treatment test.

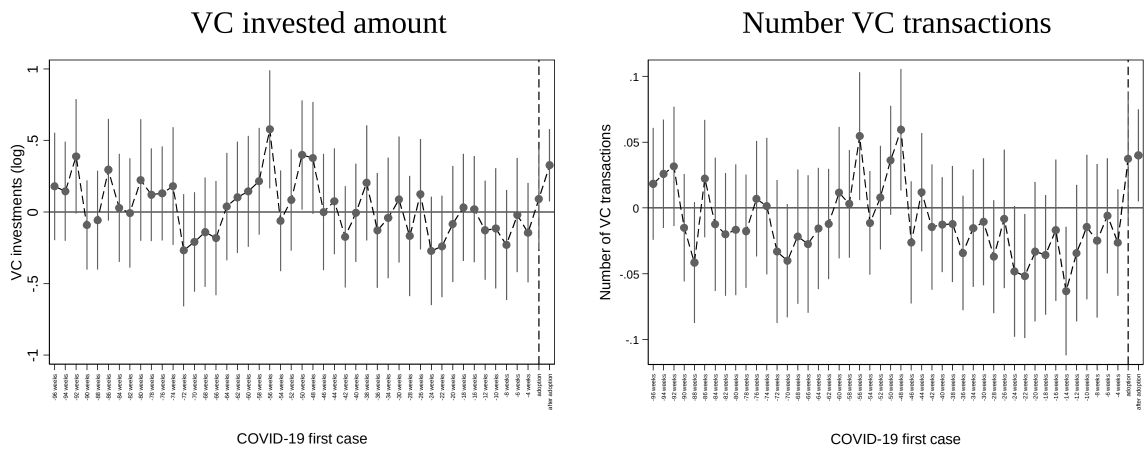
### *4.1. Common trend assumption*

A key assumption underlying the DiD analysis is the presence of common trends in the outcome variables. In our context, this means that in the absence of treatment, VC investments in pandemic-related deals would have the same trend as in non-pandemic ones. While the assumption cannot be explicitly tested, we corroborate the validity of our research design using the strategy of Autor (2003). We introduce in the baseline model outlined in equation (2) interactions of the treatment indicator and time-dummies for pre-treatment periods. If the trends are similar, these interactions should not be significant. Hence, we estimate the following specification:

$$Y_{dit} = \sum_{t=-48}^{-2} \alpha_t Pandemic_d \times First\ Case\ C_{it} + \gamma_t Pandemic_d \times First\ Case\ C_{it} + \mu_i + \tau_t + \epsilon_{dit} \quad (5)$$

The coefficients $\alpha_t$ on the pre-treatment periods, with *t* going from 48 bi-monthly periods to 2 bi-monthly periods before the first case of COVID-19 in country *i*, allow us to explore the possibility of non-parallel trends prior to outbreak. By contrast, the coefficient $\gamma_t$ shows the average effect in the post-outbreak periods. The estimates and their 90% confidence intervals, are plotted in Figure 2. The vertical dashed line indicates the point in time of treatment. The pre-outbreak coefficients are not significant, which points to the validity of the common trend assumption.

**Figure 2 Common Trend Assumption (Autor test)**




**Note:** The graphs plot the coefficients up to the treatment date and the average post-treatment effect (and their 90% confidence intervals) for the estimation of Equation (5).

## *4.2. Other robustness tests*

We perform several tests to assess the robustness of the adopted definition of pandemic-related deals. Recall that *Pandemic* is determined through a procedure that identifies as pandemic-related VC-backed transactions that contain in their deal synopses at least one word from 5 groups of keywords (biology, pharmaceutical, medicine, health, and supply chain). We check whether the results of our analyses are driven by a single group of words, by excluding one of the groups at a time, and confirm that this is not the case. We also adopt a broader definition that takes into account deals related to development of technologies intended to address needs and demands in the context of social distancing using another set of keywords in the following groups: “E-Commerce”, “Remote work”, “Information Technology and Telecommunication”, “Media and Broadcasting”. Estimating the baseline model using this new treatment, we find that the coefficients are positive and significant. We also run a model that incorporates both treatment measures and find that the coefficients on both treatments are positive and statistically significant. We conclude that the onset of the COVID-19 spread leads to significant reallocation effects for both pandemic-related deals and deals related to social distancing.

One might also argue that the text-based classification is subject to measurement errors. We pursue two strategies to mitigate this concern. On the one hand, to reduce false positives we consider a deal to be pandemic-related only if the textual fields mention more than one word from the list of keywords. We find that the coefficients are positive and significant, suggesting that our results are not driven by deals tagged as pandemic-related due to a single word, which reduces the possible effect of false positives. On the other hand, we also adopt an industry-based classification of pandemic-related deals to reduce the likelihood of false negatives. Specifically, we categorize as pandemic-related all deals in 4-digit NACE sectors with at least one pandemic-related deal from textual analysis. The effect of false negatives among the non-pandemic deals seems modest. We also perform some falsification tests using placebo treatment for periods that precede the actual treatment time.

Last, our main analysis considers the effect of the outbreak on invested amount and number of deals but we re-estimate equation (2) using as dependent variables two new measures that account for the percentage contribution, or proportion, of pandemic-related deals to the overall VC activity. Our insights about the reallocation effect of COVID-19 continue to hold in this case.

## 5. Conclusions

In this paper we explore the potential reallocation effects that could take place in the VC market following the global spread of the COVID-19 pandemic by examining how VCs shift their investment towards pandemic-related deals. Using a difference-in-differences framework, and the staggered nature of the spread of the pandemic around the world, we document significant shifts in VC investment by comparing the dynamics of pandemic-related and non-pandemic deals.

We establish a positive empirical relationship between the spread of COVID-19 and VC investment in pandemic-related deals, in terms of invested amount and number of transactions. Our findings are robust to a variety of tests related to alternative definitions of pandemic-related investment, assumptions underlying our empirical strategy, and timing conventions.

We also document several heterogenous effects underneath the average estimates, namely, that the magnitude of the reallocation effect could depend on the experience and origin of the VCs, as well as investment stage of the transaction. Thus, our analysis highlights the role of the global pandemic for the functioning of the VC market.

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## Appendix

**Table A.1 Groups of Keywords for the Strict and Broad Definitions of Pandemic-related**

| Definition | Groups | Sub-groups | Words |
|---|---|---|---|
| Strict | Biology | Biology as a discipline | Biology; Biotech; Genetic; Laboratory; Mutation; R&D Biology; Sampling; Sequencing; in Vitro |
| | | Human body | Blood; Plasma; DNA/RNA; Enzyme; Gene; Genome; Molecule; Proteine |
| | | Virus | Antibody; Antigen; Antiviral; Clonal; Monoclonal; Spike; Vaccine; Viral; Virologist; Virus |
| | Chemistry and Pharmaceuticals | Chemistry as a discipline | Chemicals; Chemistry; Molecule; Oxygen; Posology; Reagent; Receptor; R&D Chemistry; |
| | | Pharmaceutical | Biopharma; Drug; FDA; Pharma; Pharmacy; R&D Pharmaceuticals |
| | Medical Science | Disease and symptoms | Breath; Cancer; Contagious; Cough; Disease; Fever; Flu; Illness; Immune; Immunity; Influenza; Infection; Infectious; Lung; Pneumonia; Sore throat |
| | | Medicine as a discipline | Clinical; Cure; Diagnosis; Inhale; Medicine; Patient; Placebo; Preclinical; Screening; Syndrome; Symptom; Therapy; Therapeutic; Telemedicine |
| | Health | Hygiene | Epidemic; Hygiene; Pandemic, Sanitary; Sanitize |
| | | Public Health | Care; Death; Health; Health-care; Hospital; Hospitalization; Lockdown; Plague; Public health; Quarantine; Triage |
| | Healthcare Supply Chain | Medical tools | Disinfectant; Health-tech; Mask; Medical tool; Pad; Patch; Protective equipment; Respiratory; Tampon; Ventilator |
| Broad | Groups in the "Strict" definition + the following five sub-groups | E-Commerce | Delivery; E-commerce; Online commerce; Online shopping |
| | | Remote work | Remote working, Teleworking, Smart working, Smart mobility |
| | | IT & Telecommunication | Digital payment; Digital currency; E-wallet; Electronic transaction; Internet; Information Technology; Online payment; Social media; Social network; Streaming; Telecommunication; Wireless |
| | | Media and broadcasting | Broadcasting; Radio; Television; Television programming |

**Note**: The table lists the groups of keywords used to determine if a deal belongs to the pandemic-related category based on the strict and broad definitions, respectively.

**Table A.2 Examples of Pandemic-related (Non-pandemic) Deals in Non-health (Health) Sectors**

| Case | Company name | Description of the deal |
|---|---|---|
| Pandemic-related deals for firms operating in non-health sectors (1) | Pharmapacks LLC | This US company raised approximately $150M in July 2020 in a funding round led by GPI Capital LP and JP Morgan. The investment was in a deal to fund a project aimed at providing online pharmacy services, specifically related to the delivery of pharmaceutical products ordered via the web portal of the firm. Based on our textual analysis, this deal falls in the pandemic-related category. However, the NACE macro-sector of Pharmapacks is "Wholesale and retail trade", which is not directly related to healthcare. More information about the nature of the deal can be found at https://www.prnewswire.com/news-releases/pharmapacks-announces-growth-financing-by-gpi-capital-and-jpmorgan-chase-bank-301101320.html). |
| | Xiaochuan Chuhai Education Technology (Beijing) Co., Ltd | This Chinese firm raised about $750M in June 2020 from an investment team led by FountainVest Partners and Tiger Global Management. The funding was intended to facilitate development of an online education mobile application (Zuoyebang) that helps with remote learning during COVID-19 lockdown While the firm belongs to the "Information and communication" NACE macro-sector, our textual analysis considers the deal as part of the pandemic-related category. More information about the deal can be found at https://www.reuters.com/article/us-zuoyebang-fundraiisng/chinese-online-tutor-zuoyebang-raises-750-million-in-fresh-round-idUSKBN240093). |
| Non-pandemic deals for firms operating in the health sector (2) | Grupo Dental Tecnologico Mexicano SAPI de CV | This company raised two funding rounds of investments on January 27th and March 3rd, 2020. The rounds were valued $5M and $.15M, respectively, and were led by Tuesday Capital, Jaguar Ventures, Foundation Capital LLC and Y Combinator Management. The funds were to develop the provision of orthodontics services. |
| | Vision Care Connect LLC | This US-based ophthalmology firm received $.15M of seed funding in May 2019 by Jumpstart Foundry LP to provide ophthalmology services. |
| | Apricity Fertility UK Ltd | This UK-based start-up provides fertility treatment advisory services. It received €6M in June 2019 in a Series A funding round by Kamet Ventures to accelerate market entry strategy. |

**Note:** (1) These transactions involve companies in NACE sectors not related to healthcare and hospital activities that have pandemic-related projects. (2) These transactions involve companies in NACE sectors related to healthcare and hospital activities that have non-pandemic project.

**Table A.3 Test of Differences in the Means of Outcome Variables**

| Variable | All deals | | Pandemic-related deals | | Non-pandemic deals | | Means difference |
|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. | p-value |
| VC invested amount | 2.051 | 3.990 | 1.118 | 3.106 | 2.984 | 4.522 | 0.000 |
| Number VC transactions | 0.328 | 0.792 | 0.152 | 0.507 | 0.504 | 0.968 | 0.000 |

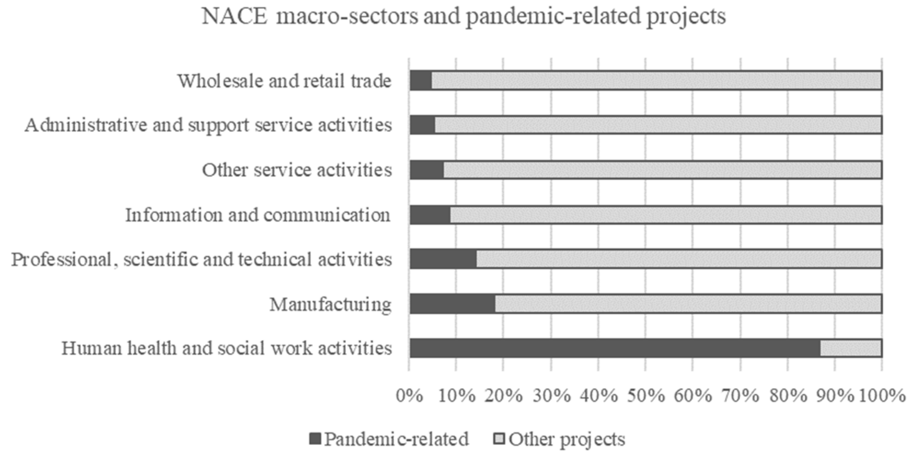
**Note**: The table presents summary statistics for the outcome variables for different groups of deals (pandemic-related vs. non-pandemic). The last column shows p-values of a t-test of equality of the means of each variable across the two groups.

**Table A.4 Baseline Results with Standard Errors Clustered at Country-Deal Category**

| | VC invested amount | | Number VC transactions | |
|---|---|---|---|---|
| Dependent Variable | (1) | (2) | (3) | (4) |
| *Pandemic* × *First Case C* | 0.272** | 0.438*** | 0.050** | 0.058** |
| | (0.125) | (0.158) | (0.023) | (0.025) |
| Observations | 15,624 | 15,624 | 15,624 | 15,624 |
| Adjusted R-squared | 0.669 | 0.661 | 0.857 | 0.859 |
| Country-Deal Category Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Country-Deal Category Trend | No | Yes | Yes | Yes |

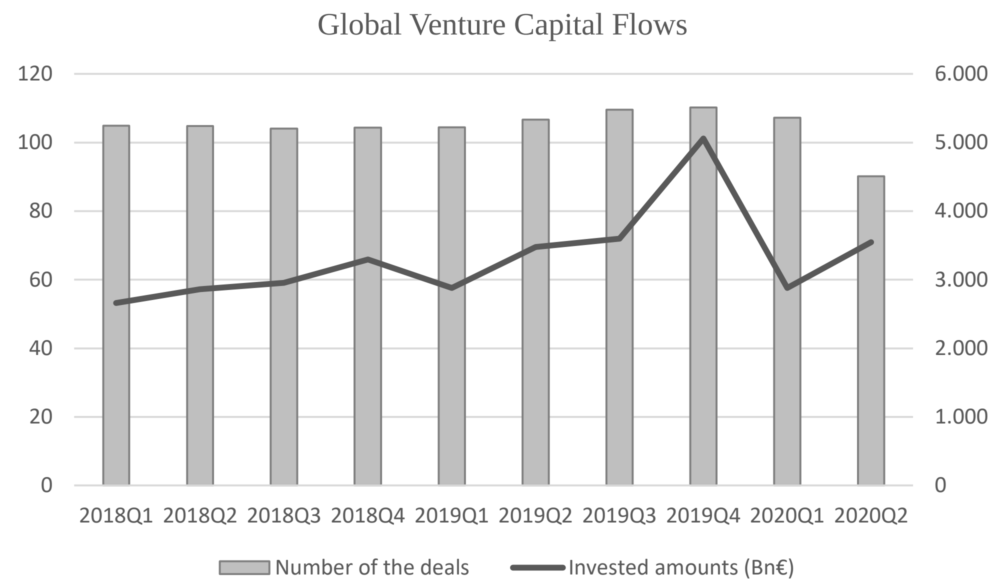
**Note**: The analysis covers 62 bi-monthly periods from 01/01/2018 to 07/31/2020 and 126 countries. *Pandemic* is an indicator that takes the value of 1 for deals that belong to the pandemic-related category, and 0 otherwise. *First Case C* is an indicator that takes the value of 1 for periods after the beginning of the spread of COVID-19 in country *c*, i.e. after the first confirmed case of COVID-19 in the country, and 0 otherwise. The table reports coefficient estimates followed by standard errors, clustered at country-deal category level, in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Figure A.1 Distribution of Pandemic-related Deals across Main NACE Macro-sectors**

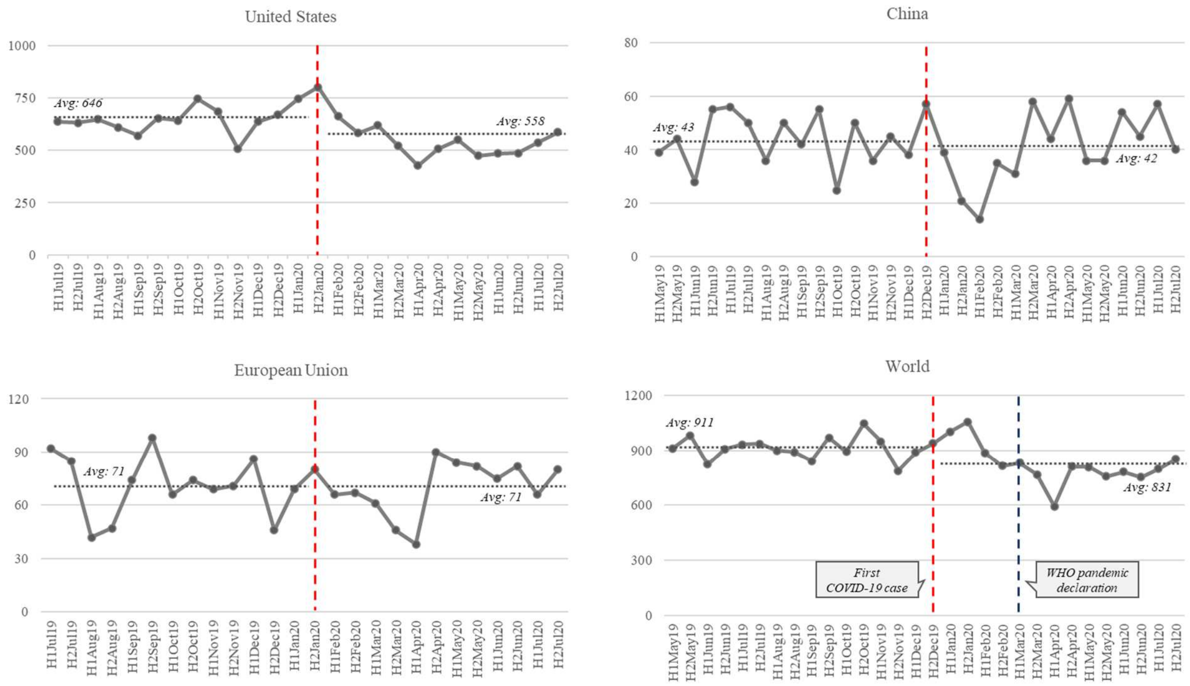



**Note:** The figure presents the share of pandemic-related deals (as a fraction of all deals) during the period from January 2018 to July 2020, by top macro-sector. Macro-sectors are identified by the "broad structure" of sectors according to NACE Rev. 2 European Commission definition (2008). Top macro-sectors are those for which the pandemic-related share is at least 5% of the total projects.

**Figure A.2 Evolution of Global VC Financing (from Q1 2018 to Q2 2020)**



## Figure A.3 Evolution of VC Financing (before and since the pandemic)




**Note**: These figures show average number of VC deals completed in the US, China, the EU, and at the worldwide level, based on data from Zephyr (Bureau van Dijk). Frequency is bi-monthly. The number of transactions (y-axis) are plotted for the same number of periods before and after the first case of COVID-19 for each unit of analysis, i.e. 15 periods (from May 2019 to July 2020) for China and the World, and 13 periods (from July 2019 to July 2020) for the US and the EU, respectively. The first cases at the EU level is based on France, which has the first case in EU in the second half of January 2020, while the first case at the World level is based on China in the second half of December 2019. The red vertical dashed lines represent the start of the COVID-19 pandemic based on first confirmed case in the country, while the dotted grey horizontal lines indicate the average bi-monthly number of deals during the pre- and post-COVID-19 periods, respectively. In the “World” panel, the blue vertical dashed line indicates the WHO pandemic declaration (H1 March 2020). The comparison between the average number of VC transactions before and since the WHO declaration is not reported in the Figure for the sake of clarity. Nevertheless, the average number of cases since the WHO declaration and up to the end of the sample (i.e. ten bi-monthly periods) is equal to 776, while the average number of cases in the ten periods before the declaration is equal to 927.