Abstract

The value of innovation during crises can be extraordinary. While higher payoffs increase the rate of innovation, they also induce a strategic distortion in its direction. We show theoretically that an increase in payoffs increases competition among inventors, inducing a shift toward less promising but quicker-to-finish inventions. Empirically, we estimate the size of the distortion using entry with vaccines versus non-vaccines, and novel versus repurposed compounds, during the Covid-19 pandemic. Our estimates suggest that a social planner would have increased the number of firms working on vaccines by 77 percent, and on novel compounds by 17 percent. Policy remedies include advance purchase commitments based on ex-ante value, targeted research subsidies, or antitrust exemptions for joint research ventures.

1 Introduction

During a crisis, such as a pandemic, a war, or an environmental disaster, time is of the essence. Inventions which help solve the crisis are very valuable, especially if they are discovered quickly. Patents, prizes, and untargeted research subsidies encourage firms to perform crisis-relevant R&D.

However, even when more firms perform research related to a crisis, do they work on the socially optimal projects? The high payoffs to crisis-relevant invention change market structure by inducing entry. Many innovation policies either subsidize effort in an untargeted way (R&D subsidies, tax breaks), or give payoffs based on the ex-post value of the invention.

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(patents, many types of prizes). Theoretically, we show that the combination of untargeted innovation policies and endogenous entry during a crisis causes inefficient equilibrium “racing” toward easy but low-value inventions, even as they raise the total quantity of R&D.

We investigate the magnitude of this effect using the case of R&D during the Covid-19 pandemic. We first document a series of stylized facts about the astounding rate, but puzzling direction, of Covid-19 research relative to other diseases and previous epidemics. Second, we propose a theory of strategic direction of innovation with endogenous entry, describing the key sources of directional inefficiency. Third, we build a flexible structural version of this model. We use the model estimates to measure the size of the inefficiency in the direction of innovation, and to simulate counterfactual scenarios. The magnitude is not small: we estimate that in the absence of directional racing, there would be 17% more firms working on novel compounds and 77% more working on vaccines between January and June 2020. Based on our findings, we discuss why some innovation policies that work well during “normal times” may be suboptimal during a crisis.

These estimates are especially surprising since the raw data on Covid-19 research reveals that the rate of both pharmaceutical projects and related academic research is an order of magnitude higher than any previous epidemic. As the Covid-19 pandemic became global in March 2020, the rate of pharmaceutical research rose even higher. This is perhaps natural given the severity of Covid-19: its death toll has far exceeded recent viral outbreaks including H1N1 (2009), Ebola (2013-2016), or Zika (2015-2016). As of August 1, 2020, there have been nearly 700,000 confirmed deaths worldwide from Covid-19. In contrast, there were 11,323 deaths from Ebola; 18,036 deaths from H1N1, and zero reported deaths from Zika within the first year of the outbreak.

This incredible rate of research does not mean that the allocation of R&D is efficient. Compared to previous epidemics, Covid-19 research pipelines are skewed towards repurposed drugs and non-vaccines. Repurposed drugs are quicker to develop but are less well-targeted (Strittmatter, 2014). Vaccines are more challenging to develop than antiviral therapies (Lurie et al., 2020). Snyder et al. (2020) estimate the expected social value of an optimal vaccine development program is on the order of $3 trillion. After Covid-19’s severity increased in early March of 2020, the relative share of repurposed drugs increased further, and the share of vaccines decreased. More importantly, we present evidence showing that even firms with prior experience developing vaccines moved away from the task of developing a Covid-19 vaccine.

Our theoretical model, extending Bryan and Lemus (2017) by incorporating endogenous
entry, provides an explanation for these facts. As crises grow more severe, the planner finds all crisis-related inventions more valuable, and needs them more quickly. To make this happen, more firms need to begin R&D related to the crisis. Optimally, each of these firms would work on the most socially-valuable solution, so it can be completed as quickly as possible. In a market equilibrium, however, they will not necessarily do so. The higher payoff for successful research across all crisis-related inventions induces entry from firms that otherwise would not find the fixed entry cost of research worthwhile to pay. Entry means the supply side for research becomes more fractured. Firms realize that by the time they invent a vaccine or finish trials on a novel compound, many partially-effective drugs will be on the market. The willingness-to-pay for vaccines ex-post is therefore less than it was ex-ante. More fractured research markets therefore cause firms to act as if they discount the future more strongly, hence firms begin to race toward quicker-to-invent but less-valuable solutions. Indeed, “[a] decade ago, after the H1N1 influenza pandemic fizzled out, the governments of America and various European countries backed out of promised contracts, leaving pharmaceutical companies holding the bag which contained hundreds of millions of dollars of development costs.”

We then take this insight to data by estimating a structural model of pharmaceutical entry in the first six months of the pandemic. Our theoretical model makes simplifications to make the nature of the strategic distortion clear, but our empirical model more flexibly handles firm heterogeneity and dynamic entry decisions. In particular, we allow the cost of working on a given project to vary across firms based on their previous research experience, and we allow firms to enter over time rather than simultaneously.

The directional inefficiency is large: a social planner would increase the number of firms working on the vaccine project by up to 77 percent, and the number of firms working on novel compounds by up to 17 percent. A directed cost subsidy toward vaccine developers equal to 31 percent of the value of a non-vaccine drug (XX of the value of a repurposed drug) fixes the directional inefficiency. Technology-netural advanced market commitments leave substantial directional inefficiency in both cases. Indeed, an AMC that pays a bonus only for vaccines equal to their ex-post social value does not fully rectify this inefficiency: firms still react to the possibility that an adequate treatment arriving before a vaccine is invented will diminish the payoff.

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2Beginning in late May 2020, large vaccine-directed subsidies began to be introduced, such as Operation Warp Speed in the United States. See https://www.hhs.gov/about/news/2020/06/16/fact-sheet-explaining-operation-warp-speed.html.
Our results contribute to three long-running literatures in innovation policy. First, we contribute to the nascent literature on innovation policy and empirical direction. Budish et al. (2015) show that there is too little R&D on diseases whose necessary clinical trials are longer, because the effective term of patent protection after a drug reaches the market is therefore shorter. In particular, public cancer research, and private cancer R&D that is permitted to use non-death outcomes in clinical trials, do not see a link between survival rates and R&D. However, private cancer R&D that must use mortality in clinical trials sees a strong negative correlation. The fixed length of patent terms therefore shifts research effort away from cancers with low mortality. Moser (2005) suggests, using evidence from 19th century World’s Fairs, that inventors in countries without strong patent protection shifted effort toward inventions which can be protected by secrecy, such as Swiss watches. While these studies demonstrate that R&D direction shifts to areas where inventor rewards are higher, to our knowledge there are no other empirical studies showing that direction is distorted indirectly by the more complex interaction of innovation policy and market structure.

Second, there is the question of how market structure relates to the rate of invention. Schumpeter famously argued that while competitive markets have static benefits, quasi-rents are important for covering the fixed costs of innovation. This debate is particularly complex when market structure is affected by innovation policy. We show, empirically and theoretically, that there is likewise an economically-consequential relationship between endogenous market structure and the direction of innovation. This relationship implies that facially-neutral policies like patents or untargeted prizes may be particularly unlikely to work as intended during crises since those policies themselves affect market structure in a negative way.

Finally, our results are related to the largely historical literature about how governments consider the tradeoffs between various innovation policies during crises. Patents arose to protect less-powerful inventors from Venetian politicking (Comino et al., 2020). Prizes were common even in the 18th century particularly to solve urgent military problems like that of longitude when sailing and the canning of food for Napoleon’s troops (Khan, 2015). The U.S. government formed a Patent Compensation Board in 1946 to buy out nuclear energy inventions in the early days of the Cold War (Shavell and Van Ypersele, 2001; Kremer, 1998). These ad-hoc policies, we argue, help more directly target the optimal rate and direction of invention in cases where existing innovation policy becomes distortionary. Just

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3 See Shapiro (2011) on whether there is in fact any daylight between the “Arrow” and “Schumpeter” perspectives on this question.

4 On the tradeoff between patents, prizes, and other inducements more generally, see, (e.g. Wright, 1983; Weyl and Tirole, 2012; Galasso, 2020).
as governments have used these special innovation schemes to avoid favoritism, commitment problems, and excess market power in critical markets, we argue that crises require particular attention to the effects of high levels of competition on R&D incentives.

2 Covid-19 Pipelines and Directional Inefficiency

In this section, we establish six stylized facts about innovation during different epidemics and within the Covid-19 epidemic over time.

First, the rate of Covid-19 drug development and academic research far exceeds previous viral outbreaks (Stylized Fact 1). Second, as the Covid-19 crisis escalated, the rate of new drug therapies in development spiked further (Stylized Fact 2). Third, this increase was largely driven by the entry of young, small, and inexperienced firms (Stylized Fact 3). Fourth, these entrants largely repurposed existing drugs or developed non-vaccine therapies relative to entrants earlier in the Covid-19 outbreak (Stylized Fact 4). Fifth, the share of repurposed and non-vaccine drug therapies is significantly larger than in previous viral outbreaks (Stylized Fact 5). Sixth, as the crisis gets worse, all firms are more likely to work on repurposed drugs and non-vaccine therapies. This holds true even for “experienced” firms—i.e., those with the capability to engage in vaccine research (Stylized Fact 6).

We use proprietary data from “BioMedTracker,” a dataset produced by Informa PLC and tracks the development history of pharmaceutical drug projects. For every pharmaceutical drug project, the dataset provides information that includes when development started, the identity of the developer, the type of drug project (e.g., vaccine or biological drug), whether it has undergone clinical trials (and when), and whether it has been approved. This information allows us to keep track of the current and past research pipelines of pharmaceutical companies. We complement these data with information from public sources, including disease-related academic publications on PubMed and information about recent viral epidemics. See Online Appendix Section A for details about the data construction.\(^5\)

\(^5\)Data in this context is rapidly evolving. Our dataset is current as of June 15, 2020. We cross-checked our data with a publicly available report by the Milken Institute on Covid-19 therapies. Both datasets track roughly the same projects in development. See the Online Appendix for more details.
Figure 1: Panel A shows the number of drug therapies in pharmaceutical pipelines, by pandemic/epidemic. Panel B shows the number of disease-related academic medical publications, by pandemic/epidemic.

A) Therapies Pipelines

B) Academic Publications

Notes: The figure plots the number of drug therapies (at all stages of development) in research pipelines, by disease. The beginning of the respective pandemics are December 1, 2019 (Covid-19), April 1, 2015 (Zika), December 1, 2019 (Ebola), and January 1, 2009 (H1N1). Covid-19 therapies measured as of June 17, 2020. The projected number of breast cancer drug therapies are provided as a reference and are computed using the formula \( \text{entry rate} \times \text{time} \), where \( \text{entry rate} \) is the average number of new breast cancer drug therapies per day between the years 2007 and 2016. The vertical line indicates March 11, 2020, the date the WHO declared a global pandemic.

2.1 The Rate of Covid-19 Research

As a consequence of the scale of the Covid-19 crisis, there has been an unprecedented response by the pharmaceutical industry and academic researchers. Figure 1 (Panel A) shows the number of new drug therapies (at all stages of development) in pharmaceutical research pipelines over time, for four viral epidemics: Covid-19, Ebola, Zika, and H1N1.\(^6\) Similarly, Figure 1 (Panel B) shows the volume of disease-related research articles in medical academic journals over time.\(^7\)

In the first seven months after Covid-19 began to spread, there are over 350 therapies in development and over 17,000 related academic publications. The rate of production of new therapies is faster than that which followed any of the three other recent viral epidemics or the average past-decade rate for breast cancer therapies.\(^8\) Forty-one of these drug therapies

\(^6\)The 2012 MERS and 2002-2003 SARS epidemics led to only a combined 25 drug therapies in the first year after these outbreaks began.

\(^7\)In our analysis, we use December 1st, 2019, as the start date of the Covid-19 outbreak. See, for instance, Wang et al. (2020).

\(^8\)Cancer in general received more NIH funding than any other disease category (NIH, 2020), and breast
Table 1: Share of repurposed and vaccine drug therapies, by disease

<table>
<thead>
<tr>
<th>Disease</th>
<th>Repurposed Count</th>
<th>Share</th>
<th>p-value</th>
<th>Vaccine Count</th>
<th>Share</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covid-19</td>
<td>178</td>
<td>.506</td>
<td></td>
<td>52</td>
<td>.230</td>
<td></td>
</tr>
<tr>
<td>Ebola</td>
<td>7</td>
<td>.333</td>
<td>0.127</td>
<td>10</td>
<td>.476</td>
<td>.041</td>
</tr>
<tr>
<td>Zika</td>
<td>1</td>
<td>.066</td>
<td>0</td>
<td>12</td>
<td>.800</td>
<td>0</td>
</tr>
<tr>
<td>H1N1</td>
<td>0</td>
<td>.000</td>
<td>0</td>
<td>14</td>
<td>.737</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: The table displays the count and share of drug therapies that are repurposed and vaccine drug therapies in the first year after the start of the viral outbreak, by disease. p-values of two-sided tests for equality of shares (disease v. Covid-19) in ‘p-value’ columns.

were already undergoing clinical trials as of June 17, 2020 (8 are at phase I, 15 at phase II, and 18 at phase III). This exceeds the total first-year number of drug therapies for Zika and Ebola, including all those that never reached clinical trials. Online Appendix Figure A.1 shows that the number of existing and planned clinical trials registered with the NIH for Covid-19 far exceeds that of previous pandemics. Likewise, the rate of academic research production on Covid-19 is substantially higher than that related to H1N1, Ebola, or Zika published in the year following their recent outbreaks. That is, the rate of Covid-19 therapy research and development, whether measured by drugs in pipelines, academic research, or therapies in clinical trials, far exceeds recent pandemics.

Examining Figure 1 (Panel A), there is a clear visual break in the rate at which therapies entered pharmaceutical pipelines roughly 100 days after the beginning of the outbreak. This coincides with the spread of large-scale community infection outside of Asia, the first large-scale regional lockdown outside of China (in Northern Italy, on March 8, 2020), and the global stock market decline (the Dow Jones lost nearly 1/3 of its value between March 4 and March 23, 2020). In the analysis that follows, we will delineate this increase in the severity of Covid-19 with the March 11, 2020 WHO declaration of a global pandemic.

cancer the most of any cancer type. Breast cancer is also the cancer with by far the most therapies entering clinical trials over the past quarter century (Nixon et al., 2017).

As we mention in the Online Appendix, H1N1 targeted therapies are conflated with other influenza therapies in our data; the number of H1N1 therapies is therefore an upper bound.

Online Appendix Table A.1 shows that Covid-19 therapies are heavily concentrated among firms based in the U.S., with 60 percent based there. Despite the crisis beginning in Asia, less than 10 percent of known therapies are being led by a firm in East Asia.

Formally, a Wald supremum test identifies this structural break as occurring on March 4, 2020. Our empirical results are robust to the precise structural break date chosen.
2.2 Direction of Innovation

We now turn to characteristics of the pipelines of firms involved in the development of Covid-19 therapies. By examining these pipelines, we can study the allocation of innovative effort across different types of projects. Vaccines, which have a high social value, are known to be more difficult to develop than antiviral therapies (Lurie et al., 2020).

Table 1 shows the share of vaccines versus other drug therapies, and the share of drugs which are repurposed. Repurposed drugs are defined as those which existed prior to the beginning of the relevant outbreak and which have multiple indications. Note that Covid-19 therapies are more likely to be repurposed, and less likely to be vaccines, than those developed for Ebola, Zika, or H1N1.

Figure 2 (Panel A) shows evolution in the development of Covid-19 vaccines versus other drug therapies. Figure 2 (Panel B) decomposes Covid-19 drug therapies into repurposed and novel therapies. The relative trend toward repurposed therapies and away from vaccines grows even stronger after the perceived severity of the pandemic increases in early March. The explosive growth in new drug therapies in Figure 2 as the pandemic spread globally is primarily driven by non-vaccine and repurposed therapeutics. In particular, the share of

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12Online Appendix Table A.2 decomposes all Covid-19 drug therapies by drug classification.
Table 2: Pipeline composition of firms by involvement in other viral outbreaks

<table>
<thead>
<tr>
<th></th>
<th>A) Covid-19</th>
<th>B) H1N1</th>
<th>C) Ebola</th>
<th>D) Zika</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vaccines</td>
<td>Antiviral</td>
<td>Infectious</td>
<td>Any of above</td>
</tr>
<tr>
<td>Vaccine</td>
<td>.287</td>
<td>.441</td>
<td>.536</td>
<td>.544</td>
</tr>
<tr>
<td>Antiviral</td>
<td>.268</td>
<td>.438</td>
<td>.534</td>
<td>.597</td>
</tr>
<tr>
<td>Infectious</td>
<td>-.019</td>
<td>-.004</td>
<td>-.003</td>
<td>.053</td>
</tr>
<tr>
<td>Any of above</td>
<td>.341</td>
<td>.503</td>
<td>.586</td>
<td>.59</td>
</tr>
</tbody>
</table>

Notes: The table compares the pipelines of different groups of firms. The first three columns (panel A) compare the Covid-19 firms (i.e., the firms that are developing a Covid-19 drug therapy project) with all other firms (i.e., firms not developing a Covid-19 drug therapy). Other columns are defined similarly, where entrants are defined as firms that developed a drug therapy for H1N1/Ebola/Zika within a year of the start of the respective epidemic. The variables ‘Vaccine’, ‘Antiviral’, and ‘Infectious’ are indicators for whether a firm has had any drug therapy in its research pipeline of that type. For example, the variable Vaccine takes the value of 1 if the firm has developed vaccines in the past. ‘Any of above’ is an indicator that takes the value of 1 if at least one of these indicators take the value 1.

vaccines among all drug therapies is 46% prior to March 11, and 19% following the pandemic declaration. Likewise, the share of non-repurposed drugs is 64% prior to March 11 and 47% thereafter.

2.3 Experience and Directional Choices

Next, we examine which firms enter drug development for different indications. Table 2 (Panel A) shows the comparison between the pre-existing pipeline of firms currently involved in the development of a Covid-19 drug therapy versus all other pharmaceutical firms in our dataset. The table shows that the firms addressing the Covid-19 pandemic are about equally likely to have developed vaccines, antivirals, and drug therapies for infectious diseases than a firm not involved in Covid-19. That is, experience with similar diseases does not seem to predict entry into the race for a Covid-19 drug therapy.

The other panels of Table 2 similarly compare the firms that did and did not develop a drug therapy for H1N1, Ebola, and Zika, respectively. The table shows that firms that developed a drug therapy during these epidemics were far more experienced both overall and in developing vaccines, antivirals, and drug therapies for infectious diseases. In addition, a comparison across panels shows that firms working on therapies for Ebola, Zika, or H1N1 were much more likely to have had experience in related diseases than the firms working on Covid-19.13

13Online Appendix Table A.3 shows that this distinction holds in a probit regression of entry on experience
### Table 3: Entrant characteristics, by repurposed/not repurposed and entry time

<table>
<thead>
<tr>
<th></th>
<th>Not Repurposed</th>
<th>Repurposed</th>
<th>Diff.</th>
<th>Before March 11</th>
<th>After March 11</th>
<th>Diff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vaccine</td>
<td>.448</td>
<td>.017</td>
<td>-.431</td>
<td>.464</td>
<td>.186</td>
<td>-.278</td>
</tr>
<tr>
<td>Repurposed</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>.357</td>
<td>.534</td>
<td>.177</td>
</tr>
<tr>
<td>Pipeline size</td>
<td>50.247</td>
<td>67.258</td>
<td>17.011</td>
<td>84.143</td>
<td>54.064</td>
<td>-30.079</td>
</tr>
<tr>
<td>Experience w/ vaccines</td>
<td>.496</td>
<td>.096</td>
<td>-.401</td>
<td>.5</td>
<td>.222</td>
<td>-.278</td>
</tr>
<tr>
<td>Experience w/ antivirals</td>
<td>.593</td>
<td>.32</td>
<td>-.272</td>
<td>.731</td>
<td>.379</td>
<td>-.351</td>
</tr>
<tr>
<td>Experience w/ infectious diseases</td>
<td>.696</td>
<td>.41</td>
<td>-.286</td>
<td>.75</td>
<td>.49</td>
<td>-.26</td>
</tr>
</tbody>
</table>

Notes: The table compares entrant covariates by timing of entry and whether the drug therapy is repurposed. An observation is a firm–drug therapy combination. ‘Vaccine’ and ‘Repurposed’ are indicators for whether the drug is a vaccine or a repurposed drug, respectively. ‘Pipeline size’ and ‘Establishment year’ are measures of firm size and age, respectively. The variables ‘Experience w/ vaccines’, ‘Experience w/ infectious diseases’, and ‘Experience w/ antivirals’ are indicators constructed based on the research pipeline of each firm. p-values of two-sided tests for equality of means in brackets.

We further examine which types of firms are repurposing and which enter only after the Covid-19 crisis becomes more severe (after the March 11th, 2020 pandemic declaration). Table 3 shows that firms that repurpose drugs are larger than those that do not repurpose drugs (17 additional therapies in their pipelines) and are less likely to be developing a vaccine (a difference of 43 percentage points). The table also shows that, relative to firms that entered earlier, late entrants have less experience with vaccines, antivirals, and with infectious diseases, and they also have a smaller pipeline, though they are not wholly inexperienced. They are younger by an average of 2.3 years. Firms that enter after March 11th are 17.7 percentage points more likely to repurpose therapies from their existing portfolio, and 27.8 percentage points more likely to develop non-vaccine drug therapies. That is, after the crisis became more severe, there was more entry of small and less experienced firms, and a change in the direction of innovation towards more repurposing and non-vaccine drug therapies.

with similar diseases even when we condition on firm size and age. For example, the table shows that prior experience developing vaccines is generally less predictive of entry into Covid-19 than entry into the other diseases.

\[14\] We note that the direction and statistical significance of the differences in firm observables in Table 3 are robust to dropping the five largest firms developing a Covid-19 drug therapy, which have developed more than 400 drug therapies each in the past and are currently developing a combined total of 16 drug therapies (either as the lead firm or a partner). The same holds true for the other results presented in this section.
Table 4: Project choice among Covid-19 entrants: Logit regressions

<table>
<thead>
<tr>
<th></th>
<th>(1) All firms</th>
<th>(2) Experienced firms sub-sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable: Vaccine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post March 11</td>
<td>-1.071***</td>
<td>-1.032*</td>
</tr>
<tr>
<td></td>
<td>(0.393)</td>
<td>(0.603)</td>
</tr>
<tr>
<td>Pipeline size</td>
<td>-0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Establishment year</td>
<td>0.074***</td>
<td>0.056*</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Experience w/ vaccines</td>
<td>3.950***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.676)</td>
<td></td>
</tr>
<tr>
<td>Experience w/ infectious diseases</td>
<td>-0.027</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.661)</td>
<td></td>
</tr>
<tr>
<td>Experience w/ antivirals</td>
<td>-0.940</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.817)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>352</td>
<td>80</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. An observation is a drug project, and the outcome variable can take one of two values: vaccine or non-vaccine drug project. ‘Post March 11’ is an indicator that takes the value 1 if the firm’s entry date is after March 11, 2020. The variable ‘Pipeline size’ measures the number of drug therapies that the firm has developed (active or inactive) prior to Covid-19. The variables ‘Experience w/ vaccines’, ‘Experience w/ infectious diseases’, and ‘Experience w/ antivirals’ are indicators constructed based on the research pipeline of each firm. The experienced firms subsample considers only firms that have had a vaccine project and a drug project for an infectious disease prior to Covid-19 in their research pipelines.

To examine whether a particular type of firm was driving the change in the direction of innovation after March 11th, we use a logit regression to uncover the relationship between project choice and firm characteristics, controlling for whether the firm entered before or after March 11th. We estimate this regression using the full sample of Covid-19 entrants and also using the subsample of firms that have had a vaccine project and a drug project for an infectious disease prior to Covid-19 in their research pipelines (henceforth, *experienced firms*). It is reasonable to assume that these experienced firms have the know-how to develop a Covid-19 vaccine, or at least they are better equipped than firms without prior experience to handle this task.

Table 4 shows the estimates of the logit regressions. The table shows a negative and statistically significant coefficient on the post March 11 dummy, which indicates that firms that enter after March 11th are less likely to work on vaccines (all else equal). This is true for all
firms (Table 4, Column 1), but also true for the subset of experienced firms (Table 4, Column 2). That is, even experienced firms were shifting away from the vaccine project after March 11, which suggests that the directional change cannot be solely attributed to the increased entry rate of inexperienced firms after March 11.

With this evidence at hand, we now propose a simple framework that explains why we may observe this directional change when the crisis becomes more severe after March 11th.

3 A Theoretical Model of Crisis Innovation

To rationalize and interpret the empirical findings in Section 2, we incorporate endogenous entry to a version of the directed invention framework in Bryan and Lemus (2017). To highlight the strategic effect that pushes firms to deviate from the efficient direction of research, the model in this section is deliberately minimal. That said, the model is flexible enough to incorporate many extensions while retaining analytic tractability. For example, when firm size is heterogeneous, firms with larger research capacity are less likely to deviate toward low-value, quick projects compared to smaller firms.

Projects: There are two projects, \( j \in \{A, B\} \), characterized by three project-specific parameters: (1) the ease of invention \( \lambda_j \); (2) the expected payoff \( \pi_{1,j} \) to the inventing firm when nothing has been invented yet; and (3) the expected payoff \( \pi_{2,j} \) to the firm that invents \( j \) if the other project has already been invented. This captures that the payoff of each project depends on the history of discoveries. For example, let the payoff of a vaccine \( A \) be 10 and of a treatment drug \( B \) be 5 when nothing has been invented yet. Once the vaccine is discovered, the marginal benefit of the drug falls to, say, 3, since less treatment is needed in a partially immunized population. Likewise, if the drug is invented first, the marginal benefit of the vaccine \( A \) may fall to 7 since effective therapeutics will lead only high-risk populations to vaccinate. In this case, \( \pi_{1,A} = 10 \), \( \pi_{1,B} = 5 \), \( \pi_{2,A} = 7 \), and \( \pi_{2,B} = 3 \).

Firms: Each firm is endowed with one perfectly divisible unit of effort. A firm that wants to enter the R&D race must pay a one-time fixed cost \( F \). Once this entry cost is paid, firms observe the number of competitors that have entered and decide how to allocate its unit of

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15Online Appendix Table A.4 shows that 76 percent of experienced firms that entered before March 11 chose to develop a vaccine, while only 51 percent of experienced firms that entered after March 11 did so.
16In Section 4, we introduce an empirical model that allows for more heterogeneity, and we quantify that the strategic effect identified in this section.
17Derivation available from the authors on request.
effort across the projects. Each firm chooses what fraction of its research capacity to allocate towards each project at each point in time. We denote by $x_{ijt} \in [0,1]$ the research effort allocated toward project $j$ by firm $i$ at time $t$.

**Timing:** Time is continuous and the discount rate is $r > 0$. All firms first simultaneously choose whether to enter. Conditional on that entry, at any given time $t$, firms simultaneously allocate their research capacity arbitrarily across available projects. The probability that firm $i$ invents $j$ before time $t$ is given by an exponential distribution of parameter $\lambda_j x_{ijt}$. This implies that the research production function is constant returns to scale on a given project.

**Crises:** We capture the severity of the crisis by, equivalently, a scaling of all payoffs (inventions become more valuable) or a reduction in entry costs (e.g., caused by reduced regulatory burdens). In more severe crises, we will show that both the planner optimal and the equilibrium number of firms entering the R&D race increases. Therefore, an increase in overall entry is empirically equivalent to an increase in crisis severity.

We make three additional assumptions to make results as stark as possible. First, we assume that the payoff of any invention equals its social surplus. That is, there is no gap between the surplus inventors earn and the social value of their inventions. Second, we assume that project $A$ is difficult, yet valuable (a long-term project), whereas $B$ is easier, yet less valuable (a short-term project). That is, $\pi_{1,A} + \pi_{2,B} > \pi_{1,B} + \pi_{2,A}$ and $\lambda_B > \lambda_A$. In the context of innovation during an epidemic, we can think of project $A$ as a vaccine or a novel drug, and project $B$ as a non-vaccine therapy or a repurposed drug. Third, we assume that $\lambda_B \pi_{1,B} > \lambda_A \pi_{1,A}$. This implies that the flow payoff of the short-run project is larger than the flow payoff of the long-run project. If this were not true, then the value of the short-run project is so low that no firm would ever work on it in equilibrium, regardless of the discount rate.

Before we move on the results, let us illustrate our main insights with a numerical example. Consider the parameters $\pi_{1,A} = 10$, $\pi_{1,B} = 5$, $\pi_{2,A} = 7$, $\pi_{2,B} = 3$, $\lambda_A = 0.0018$, $\lambda_A = 0.0055$, and $r = 0.0063$. First, suppose that only two firms enter. In that case, the optimal allocation is to have both firms work on $B$ first. Furthermore, this allocation is an equilibrium. Next,
suppose that a crisis strikes and profits scale up (or entry costs go down) such that twenty firms enter (a 10-fold increase relative to normal times). The optimal allocation now is to have all firms work on A first. This allocation, however, is not an equilibrium. When every firm works on A, each receive an expected payoff of 0.5474, while the expected payoff of deviating to B when everyone else works on A is 0.7305. Since the research market is so competitive, firms place little weight on the fact that their invention today affects the continuation value for all other firms tomorrow. That is, more competitive research markets cause firms to behave as if they discounted the future more heavily.

The key takeaways from this example are: (1) a crisis increases the number of firms that enter; (2) the socially optimal solution is more likely to entail firms working on the “hard” solution (e.g. vaccine) first; (3) the competitive pressure from entry makes firms unwilling to work on the hard solution, and firms work on an inefficient direction of innovation in equilibrium. We now formally identify how the crisis and the market structure create competitive pressure that leads to an inefficient direction of innovation.

3.1 Planner Optimum

Consider first the efficient allocation of research across projects, when \( M \) firms have entered. Following the invention of either \( j \in \{A, B\} \), the planner will allocate all the research capacity towards the remaining project, denoted by \( k \in \{A, B\} \), with \( k \neq j \). The expected social continuation value following the invention of project \( j \) is then

\[
V_j^S = \int_0^\infty \pi_{2,k} \cdot \lambda_k M e^{-\lambda_k M t} \cdot e^{-rt} dt = \frac{M \lambda_k}{r + M \lambda_k} \pi_{2,k}.
\] (1)

In this equation, \( \lambda_k M e^{-\lambda_k M t} \) is the density of the time of arrival of project \( k \) when all research capacity is allocated toward that project. Let \( P_j = \pi_{1,j} + V_j^S \) be the planner’s expected payoff when \( j \) is invented first. When nothing has been discovered yet, the planner chooses how to allocate effort across \( A \) and \( B \) to solve

\[
\max_{(x_j)_{j \in \{A,B\}}} \int_0^\infty \sum_{j \in \{A,B\}} P_j \cdot \lambda_j x_j e^{-(\lambda_A x_A + \lambda_B x_B) t} \cdot e^{-rt} dt
\]

subject to \( x_A + x_B = M \) and \( x_j \geq 0 \), for \( j \in \{A,B\} \). The probability that no innovation has arrived before time \( t \) is \( e^{-(\lambda_A x_A + \lambda_B x_B)} \), and the rate at which project \( k \) is invented is \( \lambda_k x_k \).

We begin with a lemma showing the planner optimum holding \( M \) constant.
Lemma 1. For any fixed capacity $M$:

1. The planner optimally uses all the research capacity on project $A$ first and then on project $B$ if and only if $S_A(M) \geq S_B(M)$ where

$$S_j(M) = \frac{M\lambda_j}{r + M\lambda_j} P_j.$$  \hspace{1cm} (2)

2. The condition $S_A(M) \geq S_B(M)$ is equivalent to

$$\lambda_A P_A \geq \lambda_B P_B - \Delta(M) \lambda_A P_A,$$  \hspace{1cm} (3)

where $\Delta(M) = \frac{M(\lambda_B - \lambda_A)}{r + M\lambda_A}$.

3. The condition $S_A(M) \geq S_B(M)$ is also equivalent to

$$\pi_{1,A} + \pi_{2,B} \geq \pi_{1,B} + \pi_{2,A} + \frac{r}{r + M\lambda_B} \left[ \pi_{2,B} - \pi_{2,A} + \left( \frac{\lambda_B - \lambda_A}{\lambda_A} \right) \pi_{1,B} \right],$$  \hspace{1cm} (4)

where $g(M) \geq 0$, for all $M$, and $g(\cdot)$ is strictly decreasing with $g(M) \to 0$ as $M \to \infty$.

The first part of the Lemma 1 shows that it is socially optimal to deploy all the research capacity towards the invention $j$ first, where $j$ is the invention with the largest index $S_j$.\footnote{Bryan and Lemus (2017) explain the intuition for why the planner does not simultaneously research multiple projects. Intuitively, when the research production function has either constant or increasing returns to scale, there is always a “best” research line in expectation. Mathematically, the planner problem is a linear functional with linear constraints, hence the Charnes-Cooper transformation implies the optimum is a corner solution in the related linear program.}

The second and third part of the proposition characterize necessary and sufficient conditions for $A$ to be the optimal direction. From Lemma 1 (part 3), there are two straightforward observations. First, if $r \to \infty$, the optimal direction is the project with the highest flow payoff $\lambda_j \pi_j$ (the short-term project). Second, there exists $M_A$, such that for any $M \geq M_A$, the optimal direction is that with the highest social value (the long-term project). Thus, when there is sufficient “urgency” (i.e., when $r$ is large enough), it is optimal to direct research to the short-term project. However, for any fixed level of urgency, the optimal research direction is the long-term project if enough firms have entered.

Let us now endogenize entry. Denote by $V(M) = \max_{j \in \{A,B\}} S_j(M)$ the social payoff under the efficient research direction with $M$ firms. We will assume that $V(1) \geq F$, so it is optimal
to let the at least one firm enter. The optimal number of active firms, denoted by \(M^*\), is the solution to

\[
\max_{M \in \{0, 1, 2, \ldots\}} V(M) - F \cdot M.
\]

Recall that we model a more severe crisis as a scaling of all payoffs (inventions become more valuable) or a reduction in entry costs (e.g., caused by reduced regulatory burdens).

**Proposition 1.** We have the following results:

1. If the severity of the crisis increases, it is optimal to increase the number of firms searching for a solution.
2. As the number of firms increases to a sufficiently large number, it is optimal to direct them towards the long-term project.

**Proposition 1** is intuitive. There is a higher marginal return of an additional firm in a more severe crisis because payoffs are amplified. By scaling all payoffs proportionally, a more severe crisis *does not have a direct effect* on the efficient direction of innovation, because all payoffs are scaled up by the same factor. Severe crises affect the direction of innovation *indirectly* through the endogenous choice of the optimal research capacity. Efficiency requires more firms in a more severe crisis. As the number of firms grows large, it is optimal to direct these firms toward the long-term project.

That is, in severe crises, it is optimal to have so many firms enter that discounting becomes relatively unimportant since even difficult projects will be invented quickly. As crisis get more severe, we should therefore see more entry (Stylized Facts 1 and 2), but that additional entry should be more heavily tilted toward novel drugs and vaccines (contrary to Stylized Facts 4 and 5).

### 3.2 Firm Equilibrium

In contrast to the social planner, the expected private continuation payoff after the first invention is found is

\[
V_j = \frac{1}{M} V_j^s
\]

That is, following the first successful invention, all firms can work on the remaining invention and each will invent it first with a uniform probability.
Let $a_{-ij} = \sum_{k \neq i} x_{kj}$ be the cumulative effort by firms other than $i$ on project $j$, and let $P_{ij} = \pi_{1,j} + V_{ij}$, where $i \in \{s, \ell\}$. Firm $i$'s best response solves

$$\max_{(x_{ij})_{j \in \{A,B\}}} \int_0^\infty \sum_{j \in \{A,B\}} (P_{ij} \cdot \lambda_j x_{ij} + V_{ij} \cdot \lambda_j a_{-ij}) e^{-\left(\lambda_A(a_{-A} + x_{iA}) + \lambda_B(a_{-B} + x_{iB})\right)t} \cdot e^{-rt} dt$$

subject to $x_{iA} + x_{iB} = 1$ and $x_{ij} \geq 0$, for $j \in \{A,B\}$. The probability that no innovation has arrived before time $t$ is $e^{-\left(\lambda_A(a_{-A} + x_{iA}) + \lambda_B(a_{-B} + x_{iB})\right)t}$, and the rate at which project $k$ is invented by firm $i$ is $\lambda_k x_{ik}$. If rivals discover project $k$ first, at rate $\lambda_k a_{-ik}$, firm $i$ loses the immediate payoff $\pi_{1,k}$, but can still work on the remaining invention.

Again, let us begin with a lemma holding $M$ constant and checking under what conditions large and small firms will deviate from the efficient direction.

**Lemma 2.** Suppose that the efficient research direction is project $A$ and that $M$ firms have entered. Consider an allocation where all firms are working on $A$. The firm best responds by exerting all effort on $A$, rather than deviating towards $B$, iff

$$\lambda_A P_A \geq \lambda_B P_B - \Delta(M)\lambda_A P_A + M(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A}). \quad (5)$$

Compare inequality (5) with inequality (3). The only difference is what we call the *strategic racing incentive*, captured by the term $M(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A})$. The strategic racing incentive is proportional to the difference of immediate flow payoffs and strictly increasing in the number of firms. If $\lambda_B \pi_{1,B} \leq \lambda_A \pi_{1,A}$, then inequality (3) implies inequality (5). This means that the efficient direction can be sustained as a firm equilibrium, regardless of the number of firms. However, when $\lambda_B \pi_{1,B} > \lambda_A \pi_{1,A}$ (as we have assumed), it may be impossible to sustain the efficient direction as a firm equilibrium.

The reason is that the competitive pressure between firms, reflected in the strategic racing incentive, drives them to deviate towards the short-term project when everyone else is working on the long-term project. Competing firms do not internalize that by directing their innovation effort towards the short-term project, they lower the probability that the long-term project—which is a more difficult but more socially valuable invention—is invented first by other firms. In equilibrium, then, firms will *rush* toward projects that can be finished quickly or that have a high immediate payoff.\(^{22}\) Thus, even if the *level* of R&D is efficient, in equilibrium firms may deploy their research in an inefficient direction.

\(^{22}\)This intuition is similar to the famous patent racing effect of Loury (1979). Here, instead of exerting superoptimal research effort, firms with fixed capacity shift effort suboptimally to projects where they internalize less of the total social payoff.
A crisis that rescales all payoffs (or reduces the entry cost) does not directly affect inequality (5). As in the planner optimum, a crisis affects the equilibrium direction indirectly by changing the equilibrium number of active firms. If a crisis is severe, the efficient solution entails working on the project with the highest social value rather than working on the project with the highest flow payoff. If severity increase the number of firms that enter in equilibrium, however, it will exacerbate precisely the racing incentive pulling firms in the opposite direction.

**Proposition 2.** As the crisis becomes more severe, the number of firms that enter in equilibrium weakly increases.

The equilibrium number of firms will depend on the equilibrium direction of innovation post-entry. Let $\Pi^*(M)$ be the post-entry equilibrium expected payoff in a R&D race with $M$ firms. This equilibrium payoffs is decreasing in $M$: from the perspective of any individual firm, more competition can only make things worse.

**Proposition 3.** In a severe enough crisis, there will be a directional inefficiency: the efficient solution involves working on the long-term project, but this is not an equilibrium. In this case, firms have incentives to deviate to the easier project. Furthermore, in sufficiently severe crises, the only equilibrium involves all firms working on the short-run project.

As the severity of the crisis increases, more firms will enter in the planner solution and in the firm equilibrium. For a sufficiently severe crisis, there will be a large number of firms both in the efficient solution and in equilibrium. In this case, as Lemma 1 (part 3) shows that it is efficient to direct these firms towards the long-term project. But as Lemma 2 shows, entry exacerbates the racing inventive. When the number of firms in equilibrium is large enough firms will deviate from the efficient direction.

Is there too much or too little entry? In general, there can be under- or over-entry in equilibrium due to two opposing forces. First, more firms means the waiting time until the first invention is shorter, hence all firms get to work on the next invention sooner: this is a positive externality, so the market solution will tend to under-supply firms. Second, more firms means more business stealing on the profits on all inventions: this is a negative externality, so the market solution will tend to over-supply firms.

**Proposition 4.** In severe crises, firms will over-enter in equilibrium, relative to the optimal number of firms.
When the entry of each firm involves business stealing, entry is more valuable to firms than to society (e.g. Mankiw and Whinston, 1986). In a very severe crisis, the business stealing motive overwhelms the positive externality firms impose on each other, by allowing each firm to work on the continuation project more quickly. Therefore, in severe crises, we always have excessive entry of firms compared to the planner optimum, even in the absence of excessive entry (see Proposition 3).

Let us return to our stylized facts. Equilibrium firm entry, and hence the total amount of research, indeed rises in the severity of the crisis, as in Stylized Facts 1 and 2. This occurs because firms with less capability in a research area are induced to enter by the higher payoffs, as in Stylized Fact 3. As entry increases, equilibrium is more likely to involve effort on short-term projects by some firms even when this is inefficient, as in Stylized Facts 4 and 5. Note that, in the model, the planner optimum and the firm equilibrium are identical if we shut down the strategic racing externality. Without strategic effects, then, more severe crises will counterfactually cause an increased incentives for all firms to work on long-run projects.

Our model also allow us to study the effect of non-profit research on the direction of innovation. Many non-profit entities are trying to develop Covid-19 solutions. From the perspective of a single profit-maximizing firm, the entry of rivals exacerbates the racing effect, regardless of whether they are for profit or non-profit. Thus, the entry of large non-profit organizations in the right direction may push for-profit firms to work on short-term solutions.

These empirical patterns are concerning because they are consistent with an equilibrium that involves inefficient racing behavior by firms particularly in crises. This strategic effect is consistent with the reduced-form evidence of Section 2, in particular with the estimates in Table 4. In the next section, we extend this model and allow for more flexibility to structurally estimate the extent of the directional inefficiency.

4 Estimating the Directional Inefficiency

In this section, we present an empirical model to estimate the magnitude of the directional inefficiency, which we do by using the model estimates to compare the observed equilibrium with the solution of the planner’s problem. The empirical model is based on the model

23The Milken Institute Covid-19 treatment and vaccine tracker attempts to track not just private pharmaceutical projects, but also public studies. As of May 4, 2020, they are tracking 310 projects globally. 51 of these do not have a private sector sponsor, meaning that 84 percent of Covid-19 research measured at the project level is at least partially driven by the concerns of for-profit companies.
presented in Section 3, but is more flexible in several ways so as to better match the data. First, we expand the setting in Section 3 by assuming that firms enter sequentially rather than entering simultaneously at the beginning of the game. Specifically, we assume that after one firm enters, the next firm enters at a time randomly determined by an exponential distribution of rate $\mu$. Second, we allow for different types of firms, where types are defined by the research experience of each firm prior to Covid-19. Third, we allow the cost of working on a project to be both type- and project-specific, rather than being identical for all firms and projects as in Section 3. Finally, we model an increase in the severity of the crisis as an increase in the entry rate of firms (see discussion in Section 3).

We leverage revealed preference to identify some of the key parameters of the model (e.g., $\pi_A$). Other parameters cannot be identified due to data limitations. Specifically, we cannot identify the discovery rate of the different types of projects ($\lambda_j$) because we do not observe actual discoveries in our dataset. For this same reason, we cannot identify how the discovery of project $j$ cannibalizes the payoff of the remaining project. Our solution to the first problem is to calibrate the values of the discovery rates $\lambda_A$ and $\lambda_B$ based on existing data on flow invention rates of early-stage pharmaceutical R&D by type. For the second problem, we assume in our primary estimates that the innovation race ends after any project is invented. We further show that the magnitude of inefficiency is similar under realistic assumptions about the value of additional vaccines or therapies once the initial “race” has been won.

4.1 Empirical model

There is a set of potential entrants. Each entrant has a type $\theta \in \Theta$, and the distribution of types is common knowledge. Firms enter sequentially and the difference between the arrival time of two consecutive firms is $\tau_{\text{entry}} \sim \exp(\mu)$. We assume that the type and entry time of a firm are independent random variables. Upon entry, a firm chooses whether to pursue project $A$ (vaccine) or $B$ (non-vaccine drug); the structural model for repurposed versus novel compounds is identical, so let us begin by considering the case of vaccines only, then return to repurposed drugs at the end of this section.

The cost of pursuing project $j$ for a firm of type $\theta$ is $c_j(\theta)$, which is a privately-observed random variable. As in Section 3, this is a one-time cost paid by the firm at the time of entering the competition. We assume that no more than $\bar{N}$ firms can enter per project.\footnote{This assumption replaces the heterogeneity in research capacity, making some firms better at research than others, but it also allows for project-specific heterogeneity.} \footnote{In the estimation, we assume $\bar{N} = 400$, which is the 99th percentile in the distribution of number of drug}
Additionally, for identification reasons explained above, we assume that the innovation race ends when one of the two projects is invented. In other words, the first invention fully cannibalizes the other.

When a firm enters, the relevant state variables are the number of firms pursuing each project, \((n_A, n_B)\). Firms are forward looking and they form beliefs about the evolution of future competition at the time of choosing what project they will work on. Note that a firm can work on only one project and this choice is irreversible. The expected value of pursuing project \(j\) conditional on the state variables \((n_A, n_B)\) is given by

\[
V^j_{n_A, n_B} = \frac{\lambda_j \pi_j + \mu \left( E_\theta[\Pr(A|\theta, n_A, n_B)]V^j_{n_A+1, n_B} + E_\theta[\Pr(B|\theta, n_A, n_B)]V^j_{n_A, n_B+1} \right)}{r + n_A \lambda_A + n_B \lambda_B + \mu}.
\] (6)

In Equation 6, firm \(j\) wins the race with flow probability \(\lambda_j\), in which case it receives a payoff of \(\pi_j\). With flow probability \(\mu\) a new firm enters the race before a discovery has been made. This new firm, depending on its type, will choose between \(A\) or \(B\). If the new firm chooses \(A\), the game will transition to the state \((n_A + 1, n_B)\); if the new firm chooses \(B\), the game will transition to the state \((n_A, n_B + 1)\).

An entrant of type \(\theta\) facing state variables \((n_A, n_B)\) chooses project \(A\) when

\[
V^A_{n_A+1, n_B} - c_A(\theta) > V^B_{n_A, n_B+1} - c_B(\theta),
\] (7)

where \(c_A(\theta) - c_B(\theta) \sim F_\theta\). Thus, the entrant chooses to pursue project \(A\) with probability \(\Pr(A|\theta, n_A, n_B) = F_\theta(V^A_{n_A+1, n_B} - V^B_{n_A, n_B+1})\).

Given that we impose a limit on the total number of firms that can enter each project, and that firms enter at rate \(\mu\), there is a time \(T\) such that all the firms have entered provided that no project has been invented. We can analytically compute the payoff of a firm working on project \(j\) at this time \(T\), and use these payoffs to solve the game by backward induction.\(^{26}\) We find the unique equilibrium of the game using this recursive procedure.

\(^{26}\)When no further entrants can enter the innovation race, the payoff of pursuing project \(j\) is given by

\[
V^j_{N, N} = \frac{\lambda_j \pi_j}{r + N(\lambda_A + \lambda_B)}.
\]
4.2 Estimation

In the estimation, we assume that there are two types of firms: experienced and non-experienced, so $\Theta = \{\text{Experienced, Non-experienced}\}$. We define experienced firms as those who have had a vaccine project and a drug project for an infectious disease in their research pipelines prior to Covid-19. We set the values of the rates at which the different types of projects are invented to $\lambda_A = 0.0000555$, $\lambda_B = 0.00007607$, which are calibrated based on historical data on approval times of drugs for infectious diseases.\(^{27}\) Note that these also reflect that vaccines have historically taken longer to develop (Lurie et al., 2020). We set the daily discount rate to $r = 1.1^{(1/365)} - 1$, which is a common assumption in the literature. Lastly, we make a scale normalization and set the payoff of the non-vaccine drug to 1 ($\pi_B = 1$). In this way, our estimates of the payoff of a vaccine ($\pi_A$) and the costs of developing each type of project are measured relative to the payoff of a non-vaccine drug. Note that $\pi$ are expected payoffs, so even though we impose within-class homogeneity in this expectation, the model allows different vaccines and therapeutics to vary in their ex-post value.

To capture the structural break in the entry rate of new firms, we assume that there is an exogenous (and unanticipated) change in the rate of arrival of new firms after March 11. Implicitly, this can be thought of as resulting from an unexpected shock to payoffs of all Covid-19 related invention. Similarly, we allow for an exogenous change in the composition of potential entrants, to reflect that fewer experienced firms entered after March 11.\(^{28}\) Thus, we estimate the rate of arrival of firms ($\mu$) and the share of experienced firms ($\kappa$) both before and after March 11. Also, because the likelihood function is based on Equation 7, we can only identify the difference in project-specific entry costs ($c_A(\theta) - c_B(\theta)$), so we assume that the cumulative distribution function of $c_A(\theta) - c_B(\theta)$ is given by $F_\theta(t) = ((t + 1)/2)^{\sigma(\theta)}$ with $\sigma(\theta) > 0$ and $t \in [-1, 1]$, and we estimate the parameters $\sigma(\theta)$ for each type.\(^{29}\)

In the estimation sample, a data point includes the following variables: vaccine$_j$ (indicator for choosing project $A$), time to next entry$_j$, experienced$_j$ (indicator for whether the firm has experience both in vaccine production and infectious diseases), Post March 11$_j$ (indicator for whether the firm’s entry time occurred after March 11), and ($n_{A,j}$, $n_{B,j}$) (cumulative number of entrants into projects $A$ and $B$, respectively, up to that moment of time). To construct

\(^{27}\)Specifically, to compute $\lambda_A$ and $\lambda_B$, we multiply the approval rate of drugs for infectious diseases (11.4 percent in our sample) by one over the average drug approval times of vaccines and non-vaccine drug therapies for infectious diseases.

\(^{28}\)That is, we do not model why different types of firms enter, but instead model their project choice conditional on entering.

\(^{29}\)The expected cost difference of a firm of type $\theta$ is given by $(\sigma(\theta) - 1)/(1 + \sigma(\theta))$. This distribution bounds the cost differences to be between -1 and 1, i.e., cost differences cannot be greater than $\pi_B$ in absolute value.
the likelihood function, we make use of Equation 7 to determine the probability that a firm of type $\theta$ facing state variables $(n_A, n_B, \emptyset)$ chooses project $A$ as well as the parametric assumptions on the distribution of entry times (exponential distribution) and distribution of types (discrete distribution).

The probability that there is no discovery in $[0, \tau]$, the next firm enters at time $\tau$, its type is $\theta$, and this new entrant works on a vaccine (project $A$) is given by

$$e^{-(\lambda_A n_A + \lambda_B n_B)\tau} \cdot \mu e^{-\mu \tau} \cdot \kappa(\theta) \cdot F_\theta(V^A_{n_A+1, n_B} - V^B_{n_A, n_B+1}).$$

More generally, the log-likelihood function of a data point is given by

$$l_j(\delta) = \text{vaccine}_j \cdot \log(F_\theta(V^A_{n_A+1, n_B} - V^B_{n_A, n_B+1})) + (1 - \text{vaccine}_j) \cdot \log(1 - F_\theta(V^A_{n_A+1, n_B} - V^B_{n_A, n_B+1}))$$

$$+ \text{After March 11}_j \cdot \log(\mu_{\text{After March 11}}) - \mu_{\text{After March 11}} \cdot \text{time to next entry}_j$$

$$+ (1 - \text{After March 11}_j) \cdot \log(\mu_{\text{Before March 11}}) - \mu_{\text{Before March 11}} \cdot \text{time to next entry}_j$$

$$+ \text{After March 11}_j \cdot (\text{experienced}_j \cdot \log(\kappa_{\text{After March 11}}))$$

$$+ (1 - \text{experienced}_j) \cdot \log(1 - \kappa_{\text{After March 11}}))$$

$$+ (1 - \text{After March 11}_j) \cdot (\text{experienced}_j \cdot \log(\kappa_{\text{Before March 11}}))$$

$$+ (1 - \text{experienced}_j) \cdot \log(1 - \kappa_{\text{Before March 11}})),$$

where the value functions implicitly take into account the changes in entry rate and composition of types after March 11. The MLE estimator of the model parameters is then given by

$$\hat{\delta} = \arg \max \sum_j l_j(\delta),$$

where $\delta = (\pi_A, \mu_{\text{Before/After March 11}}, \sigma_{\text{Experienced/Non-experienced}}, \kappa_{\text{Before/After March 11}})$.

The identification of the parameters of the distribution of entry times or types of firms is straightforward as these variables are readily observed in the data. The identification of the parameters of the cost distribution of each type of firm is possible given the assumption that the value differential of choosing project $A$ instead of $B$ (i.e., $V^A_{n_A+1, n_B} - V^B_{n_A, n_B+1}$) does not depend on firm type. Hence, the rate at which each type of firm chooses project $A$, given value differentials, identifies the parameters of the cost distributions. Lastly, we leverage revealed preference to identify the payoff of the vaccine project, $\pi_A$. Although the “racing” incentive pushes firms to choose project $B$ (the easy project), we observe firms choosing project $A$ despite facing significant levels of competition. The one parameter in the model
Table 5: MLE estimates of the parameters of the model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>St. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_A$</td>
<td>40.434</td>
<td>15.336</td>
</tr>
<tr>
<td>$\pi_B$ (normalized)</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>$\mu_{\text{Before March 11}}$</td>
<td>0.550</td>
<td>0.074</td>
</tr>
<tr>
<td>$\mu_{\text{After March 11}}$</td>
<td>3.382</td>
<td>0.198</td>
</tr>
<tr>
<td>$\sigma_{\text{Non-experienced}}$</td>
<td>3.640</td>
<td>0.412</td>
</tr>
<tr>
<td>$\sigma_{\text{Experienced}}$</td>
<td>1.004</td>
<td>0.208</td>
</tr>
<tr>
<td>$\kappa_{\text{Before March 11}}$</td>
<td>0.446</td>
<td>0.066</td>
</tr>
<tr>
<td>$\kappa_{\text{After March 11}}$</td>
<td>0.188</td>
<td>0.023</td>
</tr>
<tr>
<td>$N$</td>
<td>347</td>
<td></td>
</tr>
<tr>
<td>$\sum_j l_j(\hat{\delta})/N$</td>
<td>-0.516</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard errors computed based on the asymptotic distribution of the MLE estimator. Calibrated parameters: $\lambda_A = 0.0000555$, $\lambda_B = 0.00007607$, and $r = 1.1^{1/365} - 1$ (time is expressed in days in the model).

that can rationalize these choices is $\pi_A$.

4.3 Results

Table 5 shows the model estimates. The estimated value of a vaccine is 40.4 times the value of a non-vaccine therapy. Before March 11, the rate of entry is estimated to be 0.6 (or one firm entering on average every 1.8 days), whereas after that date, the entry rate jumped to 3.4 (or one firm entering on average every 0.3 days). Before March 11, 44.6 percent of firms were experienced, whereas the share of experienced dropped to 18.8 percent after that. The estimates of the cost distributions suggest that the expected cost difference between the vaccine and non-vaccine projects is 0.53 and -0.07, respectively, for non-experienced and experienced firms.\(^{30}\)

To gauge model fit, Figure 3 plots the raw data versus the predictions of the model for the number of vaccine and non-vaccine projects over time. We compute the model predictions by running 25,000 simulations of the model using the estimated parameters. As the figure shows, the model matches closely the number of firms in each project at every moment time.

Using the model estimates, we also solve for the socially efficient allocation of firms across

\(^{30}\) A motivation for estimating these parameters using revealed preference is that there are no highly-credible estimates of, for instance, the expected value of a Covid-19 therapeutics. Even when there are specifics - Gouglas et al. (2018) use confidential industry data to estimate that vaccine development between preclinical and Phase 2 trials costs an average of $31 to $68 million - mapping those estimates into our firm-specific cost estimates is not at all obvious.
Figure 3: Number of vaccine and non-vaccine drug therapies predicted by the model and in the data.

Notes: Outcomes for the firm equilibrium are computed based on the average outcomes across 25,000 simulations of the game.

projects. In this exercise, the social planner controls whether to allocate each entrant to projects A or B, but cannot control the rate of entry of firms. When computing the planner’s solution we assume that the social surplus of invention \( j \) is either equal to its private value or we use the rough estimate in Kremer (1998) that, if willingness to pay for therapies is proportional to income, the social surplus of a medical invention is \( 2.7x \) the fixed-price revenue of a monopolist inventor.\(^{31}\) As before, we run 25,000 simulations of the social planner’s problem and compute the outcomes for each simulation.

Table 6 presents averages across these simulations and compares them to the expected outcomes in the firm equilibrium. When assuming that the social surplus of each invention equals its private value, the analysis suggests that the social planner would increase the number of firms working on the vaccine project by 3.4%, or roughly three firms. However, assuming the social surplus of all Covid inventions is \( 2.7x \) their private value, the planner would increase the number of firms working on the vaccine by 62 firms (77%). Among the firms that are reallocated to work on the vaccine project, a majority of them are experienced firms.\(^{32}\)

We next make use of the model estimates to quantify the impact of two sets of policy interventions. First, we ask what directed subsidy for vaccine entrants would induce the

\(^{31}\)This estimate comes from assuming that willingness to pay for medical treatment is proportional to income. Using U.S. income distribution data, the gap between the total surplus of a medical invention and the profit earned by a fixed-price monopolist is 2.7.

\(^{32}\)The share of experienced firms working on the vaccine project increases by 2.4 percentage points, whereas the share of non-experienced firms only increases by 1.8 percentage points.
optimal balance of vaccines and non-vaccines given estimated firm capabilities. Second, we consider advanced market commitments (AMCs) which pay successful inventors the full ex-post social surplus of their inventions, or which only pay vaccine inventors that surplus while non-vaccine inventors earn only the fixed-price monopoly surplus.

Panel B of Table 6 shows that an entry cost subsidy equivalent to 1.8% of the value of the non-vaccine project \( \pi_B = 1 \) would induce optimal direction choice if the firms are capturing the full social surplus of their inventions. Panel C shows that if the social value of Covid-19 inventions is 2.7x their private value, and hence the directional distortion is very large as noted above, a vaccine-specific entry cost subsidy equal to 31.3% of \( \pi_B \) is needed. Panel D shows that an AMC promising to pay the first inventor of any Covid-19 invention a subsidy equal to the social surplus of their invention leads to 20% too few firms working on vaccines. Paying the AMC only if a vaccine is invented first helps, but still leaves 17% too few firms choosing to work on vaccines. To achieve efficiency with an AMC, the AMC would need to pay 3x the private value of the vaccine and be paid only if a vaccine is invented first. However, achieving efficiency with an AMC is more expensive than with directed cost subsidies (\$121.29 \pi_B \) versus \$44.77 \pi_B \). Effectively, the underprovision of vaccines is being driven by the rational expectation that some other firm will finish a moderately useful therapeutic quickly, hence large directed entry subsidies which prevent other firms from deviating are a cheaper method of preventing directional distortion.

Note where the structural model grants flexibility. Both the relative fixed costs of beginning R&D on a vaccine instead of a therapeutic, and implicitly the overall payoff of a Covid-19 related invention, are allowed to vary across firms depending on their experience with vaccines and infectious diseases. The estimates do in fact imply that payoffs were relatively high for experienced firms in the early days of the pandemic, hence their high entry share. They also imply that those firms face nowhere near the cost disadvantage of working on vaccines that less experienced firms face.

The model does not bake in a necessary racing externality to explain the data. In Online Appendix Figure A.2, we show the results of solving the model shutting down strategic effects; that is, firms enter assuming they are the first entrant, and that no firms will enter in the future, but otherwise the model is equally flexible. The mean squared error of this model is 2.6 times higher than our full model. The difference between the full model and a

\[ \text{Recall that firm heterogeneity is modeled by differing entry costs for vaccines for experienced firms, estimated via revealed preference. Note also that in these counterfactuals, we do not allow the number of firms who enter to vary (} \mu \text{ is an estimated parameter held constant in the counterfactual). The counterfactuals should therefore be interpreted as estimates for fixing directional distortion conditional on entry.} \]
Table 6: Planner’s solution versus firm equilibrium

<table>
<thead>
<tr>
<th></th>
<th>Number of firms working on:</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>vaccine project (A)</td>
<td>non-vaccine project (B)</td>
</tr>
<tr>
<td><strong>A. Data and model predictions</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>81</td>
<td>266.260</td>
<td></td>
</tr>
<tr>
<td>Firm equilibrium (model predictions)</td>
<td>80.740</td>
<td>266.260</td>
<td></td>
</tr>
<tr>
<td><strong>B. Counterfactuals when setting the social payoff of project j to π_j</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm equilibrium w/ directed cost subsidy of 0.018 · π_B</td>
<td>83.472</td>
<td>263.528</td>
<td></td>
</tr>
<tr>
<td>Planner’s solution</td>
<td>83.425</td>
<td>263.575</td>
<td></td>
</tr>
<tr>
<td><strong>C. Counterfactuals when setting the social payoff of project j to 2.7 · π_j</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm equilibrium w/ directed cost subsidy of 0.313 · π_B</td>
<td>143.129</td>
<td>203.871</td>
<td></td>
</tr>
<tr>
<td>Planner’s solution</td>
<td>143.048</td>
<td>203.952</td>
<td></td>
</tr>
<tr>
<td><strong>D. Counterfactuals when making use of AMCs</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm equilibrium w/ AMC of 2.7 · π_j for both projects</td>
<td>134.036</td>
<td>212.964</td>
<td></td>
</tr>
<tr>
<td>Firm equilibrium w/ AMC of 2.7 · π_j for the vaccine project only</td>
<td>135.651</td>
<td>211.349</td>
<td></td>
</tr>
<tr>
<td>Firm equilibrium w/ AMC of 3 · π_j for the vaccine project only</td>
<td>143.246</td>
<td>203.754</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Outcomes are measured at 188 days since December 1, 2019. Outcomes for the firm equilibrium and planner’s solution are computed based on the average outcomes across 25,000 simulations of the game. Firm equilibrium w/ directed cost subsidy indicates the case where project A receives a cost subsidy equivalent to the amount indicated in the table. Firm equilibrium w/ AMC of 2.7 · π_j indicates the case when the firm inventing project j receives a payoff of 2.7 · π_j instead of just π_j.

nonstrategic model is especially salient when it comes to early entry. As the number of firms who have entered grows large, and no invention has yet arrived, the expected payoff for any invention becomes small due to the high level of competition. Cost differentials therefore begin to drive project choice, and hence nonstrategic models will fit well. However, when few firms have entered, an expectation that the next few firms will work on a quick therapeutic will have a substantial effect on the expected value of working on a vaccine.

Although our main estimates concern vaccines versus non-vaccines, in Online Appendix Table A.5, we replicate our analysis redefining the two possible projects to be a novel drug (project A) and a repurposed drug (project B). As in Section 2, a repurposed drug is defined as one that has more than one indication and which existed prior to the Covid-19 pandemic. A novel drug is one that is not repurposed. Based on historical data on drug approval times, we set the values of λ_A and λ_B to 0.00006825 and 0.00009859, respectively. The value of r and the definition of experienced firms are the same as those used for the vaccine/non-vaccine drug analysis with which we lead this section. Underprovision of novel compounds is less severe than that of vaccines. A planner would increase the number of novel compounds by 1.5%, or by 17.0% if the social value of inventions were 2.7x the private value.

In Online Appendix Table A.6, we replicate our main analysis assuming that secondary
inventions retain some value rather than being worth nothing following the first successful Covid-19 invention. In particular, let $\delta \pi_j$ be the value of invention $j$ once the first invention of either type is invented, with $\delta < 1$. Assume that no further firm entry occurs after the first invention. We then assume that inventors working on invention $j$ at the time the first Covid-19 invention occurs receive the expected discounted payoff of one additional invention per type, where this expectation depends on the number of firms working on each invention and the difficulty $\lambda_j$. Letting $\delta = .1$ or $.5$ as in the Appendix Table does not substantially affect the degree of directional inefficiency. We interpret this as a robustness check ensuring that the assumption that only the first Covid invention earns all payoffs from the “race” is not too distortionary.

5 Discussion and Implications

Although the rate of Covid-19 research is proceeding at an unprecedented historical pace, it has involved more research on short-term solutions than previous epidemics. This trend was exacerbated when Covid-19 became a global pandemic in March 2020. Our theoretical model provides an explanation: innovation policy when payoffs are sufficiently high distort the direction of research by endogenously affecting market structure. Firms do not internalize the fact that their invention today lowers the continuation value of future inventions by other firms. The more fractured the market for research, the less any one firm weighs the total value of the market against the profits that can earned by deviating to invent a simpler, less valuable product. The high payoff of crises induce firms to enter. Therefore, strategic interaction in the highly competitive crisis market for invention leads to too much work on “quick” projects like repurposed drugs and too little work on long-run projects like vaccines. In our structural model, we show that this distortion is highly consequential economically.

The distortion we identify is *ex-ante*: it shifts what firms invent rather than the deadweight loss they generate ex-post if, for example, they have a patent. This distortion holds even though we assumed that the payoff to inventors was exactly equal to the social surplus of their invention. Prior research suggests that vaccines may be underprovided due to the difficulty of extracting this surplus. For instance, Kremer and Snyder (2015) argue that for rare but serious diseases, when consumer valuation for treatment is highly heterogeneous, it is easier to extract this surplus with treatments than vaccines. We have assumed away this possibility by giving inventors the entire social surplus, yet vaccines are still underprovided. Vaccines may also be underprovided due to a commitment problem on the part of the government.
Kremer et al. (2020) argue for advance purchase commitments partly on these grounds: pharmaceutical firms otherwise believe their vaccines will be expropriated after the cost of research has been incurred.\textsuperscript{34}

These are important concerns. Nonetheless, we suggest that policymakers during a crisis concern themselves not only with the size of the payoff ex-post inventors receive, but also on how the land rush into crisis R&D affects which projects inventors will pursue. A firm that produced a foolproof Covid-19 vaccine or a partially effective therapeutic at the peak of the pandemic would have countries bidding richly for the first batches. Nonetheless, if so many firms are working on the therapeutic that it surely will appear within a few months, potential vaccine inventors may rationally abandon that long-run project under the correct belief that the vaccine will have lower ex-post value. Technologically neutral policy in the face of strategic behavior is not in fact neutral.

Our model, both theoretical and structural, applies to problems beyond Covid. Consider a wartime government hoping to incentivize new aircraft, or an IGO that wants to see effective novel climate change mitigation technology. Assume that they credibly commit to pay the full, ex-post social value of any completed invention within their bailiwick. Doing so may be \textit{worse} than paying lower rewards if the induced competition pushes firms to work on second-best technology that can be completed quickly. Our structural model permits retrospective analyses of these distortions even when the value of different inventions is unknown to the analyst, since we draw on the revealed preference of inventors to infer the magnitude of any distortions.

What can be done? Patent buyouts (Kremer, 1998), where the government buys a patent in order to remove the deadweight loss of monopoly pricing, do not solve our problem. Indeed, by increasing the return of crisis inventions, it induces more entry and makes our ex-ante distortion worse. The same is true of generic research subsidies. The fundamental problem is that the government needs to simultaneously induce entry \textit{and} prevent the firms that enter from deviating to quick, low-value projects.

Three policies will limit this problem. First, the government can allow research joint ventures without antitrust restrictions. Note from the model that larger firms are less likely to deviate, and that the total social surplus for the industry is decreasing in the extent of deviation. In April 2020, Sanofi and GlaxoSmithKline, normally rivals, formed a joint research venture to

\textsuperscript{34}In an early book on the economics of Covid-19, Gans (2020) discusses in more depth the use of AMCs and the problem of commitment in previous epidemics.
develop a Covid-19 vaccine. Research joint ventures on projects that are expected to be harder to invent that most inventions in a sector ought to be encouraged.

Second, targeted subsidies, incentivizing only difficult, high-value remedies to the crisis, while permitting unsubsidized research on other projects, simultaneously induce entry and incentivizes firms to work on socially optimal projects. Targeted subsidies generally have a bad name: many innovation scholars do not like the government to “pick winners”. In crises, however, the nature of high-value inventions is often widely known. There is no ambiguity, for instance, about the therapeutic properties of the highest-value remedies for Covid-19. To this end, Table 6 shows that a vaccine-specific cost subsidy of 31 percent of the value of non-vaccines \( \pi_B = 1 \) would fix the directional inefficiency. We use data only through June 6, 2020 because targeted subsidies toward vaccines became a major part of the policymaker arsenal with the announcement of “Operation Warp Speed” subsidies. This shift was not ex-ante obvious: indeed, a group of prominent economists argued in the May 4th, 2020 issue of the New York Times discussed existing large subsidy programs for Covid-19 inventions, but noted that they were targeted broadly at “diagnostics, therapeutics, and treatments” (Athey et al., 2020).

Finally, advanced market commitments (AMCs) can be used, with a twist. The reason firms deviate to short-run solutions is partly because the marginal value of the ex-ante best project falls once partial remedies exist. This collapse may not be linear. For instance, imagine that a partially effective drug is half as good as a vaccine from the perspective of a government. Once the drug exists, firms will consider whether to keep working on the vaccine and receiving this lower payment, or to work on some outside option. Reasoning that when other firms are working on the drug, the probability of finishing a vaccine first is quite low, all firms will eventually deviate to working on the drug, and the vaccine will not be invented. An AMC committing to pay the ex-ante social value of an invention, even if future inventions lower their value, can completely remedy directional inefficiency. Estimates of the value of targeted Covid-19 vaccine AMCs argue that an advance commitment of nearly $40 billion, with coordinated allocation to high risk populations, increases welfare by avoiding ex-post bidding wars for potentially limited vaccine supplies (Snyder et al., 2020). Our results suggest that optimal vaccine AMCs, or alternatively vaccine cost subsidies, need to be higher yet given the strategic distortions induced by high overall Covid-19 payoffs.

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36See Grossman and Shapiro (1986) for a deeper analysis of the antitrust issues with research collaborations.
6 References


32
Online Appendix

Innovating During a Crisis: Evidence from Covid-19

Supplemental Material – Intended for Online Publication
A Data Sources and Data Construction

We use proprietary data from “BioMedTracker,” which is an Informa PLC product and tracks pharmaceutical pipelines over time. We also retrieved lists of medical research articles by disease from PubMed to study the evolution of the volume disease-related academic publications around the time of an epidemic/pandemic.

We use BioMedTracker (last accessed June 15, 2020) to obtain the full list of Covid-19 drug therapies in development as well as the development history (i.e., the start dates of development and clinical trials if applicable) and the list of companies involved in the development of each drug therapy. Similarly, we use BioMedTracker to obtain the same information for the H1N1 pandemic (2009), the Ebola epidemic (2013-2016), and the Zika epidemic (2015-2016). We also use BioMedTracker to obtain the pipelines (i.e., the list of all drugs that are currently in development or have been in development in the past) of all pharmaceutical companies.

With few exceptions, the variables we use in the analysis are variables that are available in the raw BioMedTracker data. We define the variable ‘Repurposed,’ as any drug for disease $x$ that existed prior to the beginning of the epidemic of disease $x$ (e.g., a repurposed Covid-19 drug is one that has multiple indications and existed prior to December 1, 2019). We also define variables related to the drug-development experience of firms (i.e., “experience w/ vaccines”, “experience w/ antivirals”, and “experience w/ infectious diseases”), which are based on the research pipeline of each firm.

There are, of course, many other datasets on Covid-19 projects. Hand-checking these data reveal that they generally overlap heavily with the BioMedTracker data. For instance, the Milken Institute Covid tracker based on public media reports as of April 20, 2020, finds 146 drug treatments and 92 candidate vaccines, of which 49 are not modified existing platforms.$^{37}$ As of April 20, 2020, BioMedTracker finds 170 drug treatments and 51 candidate vaccines. For reasons of comeasurability with the Ebola, Zika, and H1N1 data, we use only the remedies in the BioMedTracker dataset.

### B Additional Tables and Figures

#### Table A.1: Covid-19 firms, by country

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>4</td>
<td>1.14</td>
<td>1.14</td>
</tr>
<tr>
<td>Austria</td>
<td>4</td>
<td>1.14</td>
<td>2.28</td>
</tr>
<tr>
<td>Belgium</td>
<td>4</td>
<td>1.14</td>
<td>3.42</td>
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<td>Canada</td>
<td>19</td>
<td>5.41</td>
<td>8.83</td>
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<td>10</td>
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<td>Denmark</td>
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<td>2.28</td>
<td>20.51</td>
</tr>
<tr>
<td>Italy</td>
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<td>1.14</td>
<td>21.65</td>
</tr>
<tr>
<td>Japan</td>
<td>10</td>
<td>2.85</td>
<td>24.50</td>
</tr>
<tr>
<td>Korea (South)</td>
<td>10</td>
<td>2.85</td>
<td>27.35</td>
</tr>
<tr>
<td>Netherlands</td>
<td>4</td>
<td>1.14</td>
<td>28.49</td>
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<td>Norway</td>
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<td>0.28</td>
<td>28.77</td>
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<tr>
<td>Russia</td>
<td>2</td>
<td>0.57</td>
<td>29.34</td>
</tr>
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<td>Scotland</td>
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<td>0.28</td>
<td>29.63</td>
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<td>Spain</td>
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<td>1.42</td>
<td>31.05</td>
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<td>1.42</td>
<td>32.48</td>
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<tr>
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<td>0.28</td>
<td>36.47</td>
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<tr>
<td>United Kingdom</td>
<td>12</td>
<td>3.42</td>
<td>39.89</td>
</tr>
<tr>
<td>United States</td>
<td>211</td>
<td>60.11</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Notes: The table shows the distribution of locations of Covid-19 firms (i.e., the firms that are leading a Covid-19 drug therapy project).
Table A.2: Covid-19 drug therapies, by drug classification

<table>
<thead>
<tr>
<th>Type</th>
<th>Not repurposed</th>
<th>Repurposed</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biologic</td>
<td>60</td>
<td>62</td>
<td>122</td>
</tr>
<tr>
<td>Device</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>New Molecular Entity (NME)</td>
<td>19</td>
<td>99</td>
<td>118</td>
</tr>
<tr>
<td>Non-NME</td>
<td>12</td>
<td>13</td>
<td>25</td>
</tr>
<tr>
<td>Unknown</td>
<td>2</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Vaccine</td>
<td>78</td>
<td>3</td>
<td>81</td>
</tr>
<tr>
<td>Total</td>
<td>171</td>
<td>178</td>
<td>349</td>
</tr>
</tbody>
</table>

Notes: The table shows the number of new Covid-19 drug therapies (at all stages of development) by drug classification for both repurposed and non-repurposed drugs. Repurposed drugs are defined as drug therapies that existed prior to December 1, 2019 (i.e., beginning of the Covid-19 pandemic) and has more than one indication (e.g., Covid-19 and Ebola).

Table A.3: Probability of entry on pipeline composition: Probit regressions

<table>
<thead>
<tr>
<th>Experience w/ vaccines</th>
<th>Covid-19</th>
<th>Ebola</th>
<th>H1N1</th>
<th>Zika</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.314***</td>
<td>0.346*</td>
<td>0.824***</td>
<td>1.255***</td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.208)</td>
<td>(0.212)</td>
<td>(0.223)</td>
</tr>
<tr>
<td>Experience w/ antivirals</td>
<td>0.555***</td>
<td>0.500*</td>
<td>0.630**</td>
<td>4.419***</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.260)</td>
<td>(0.268)</td>
<td>(0.163)</td>
</tr>
<tr>
<td>Experience w/ infectious diseases</td>
<td>0.108</td>
<td>0.632**</td>
<td>0.087</td>
<td>-3.595***</td>
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<tr>
<td></td>
<td>(0.125)</td>
<td>(0.298)</td>
<td>(0.243)</td>
<td>(0.251)</td>
</tr>
</tbody>
</table>

Controls: Firm age, firm size

Observations 3475 2237 1516 2625

$R^2$

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. The table shows estimates predicting entry into the respective diseases, considering the full set of firms that have been active up until two years after the start of the respective viral outbreak. The variables ‘Experience w/ vaccines’, ‘Experience w/ antivirals’, and ‘Experience w/ infectious diseases’ are indicators for whether a firm has had any drug therapy in its research pipeline of that type prior to the respective epidemic. For example, the variable ‘Experience w/ vaccines’ takes the value of 1 if the firm has developed vaccines in the past. Firm size is defined as the number of drug therapies that the firm has developed (active or inactive).
Table A.4: Project choice among Covid-19 entrants (experienced firms subsample)

<table>
<thead>
<tr>
<th></th>
<th>Before March 11</th>
<th>After March 11</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-vaccine</td>
<td>6</td>
<td>27</td>
<td>33</td>
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<tr>
<td>Vaccine</td>
<td>19</td>
<td>28</td>
<td>47</td>
</tr>
<tr>
<td>Total</td>
<td>25</td>
<td>55</td>
<td>80</td>
</tr>
</tbody>
</table>

Notes: An observation is a drug project, and the outcome variable can take one of two values: vaccine or non-vaccine drug project. Experienced firms are the firms that have had a vaccine project and a drug project for an infectious disease prior to Covid-19 in their research pipelines. ‘Before/After March 11’ are indicators that take the value 1 if the firm’s entry date is after March 11, 2020.

Table A.5: Planner’s solution versus firm equilibrium: Repurposed vs. non-repurposed drugs

<table>
<thead>
<tr>
<th></th>
<th>Number of firms working on:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>non-repurposed project (A)</td>
</tr>
<tr>
<td>Data</td>
<td>169</td>
</tr>
<tr>
<td>Firm equilibrium (model predictions)</td>
<td>169.562</td>
</tr>
<tr>
<td>Planner’s solution (social payoff, ( \pi_j ))</td>
<td>172.095</td>
</tr>
<tr>
<td>Planner’s solution (social payoff, ( 2.7 \cdot \pi_j ))</td>
<td>198.428</td>
</tr>
</tbody>
</table>

Notes: The estimates of the parameters of the model are \( \hat{\pi}_A = 17.857 \), \( \sigma_{\text{Non-experienced}} = 1.443 \), \( \sigma_{\text{Experienced}} = 0.389 \), and the parameter estimates of the entry rate of firms and the distribution of firm types are identical to those in Table 5. The values of \( \lambda_A, \lambda_B, \) and \( r \) are set at 0.00006825, 0.00009859, and 1.11/365 – 1, respectively. As in Table 5, the values of \( \lambda_j \) are calibrated based on historical data on drug approval times. The definition of experienced firms are identical to those used in the vaccine/non-vaccine drug analysis in Table 5. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the firm equilibrium and planner’s solution are computed based on the average outcomes across 25,000 simulations of the game.

Figure A.1: Number of clinical trials registered with clinicaltrials.gov, by pandemic/epidemic

Notes: The figure plots the number of clinical trials (all stages) during the first year after the start of the viral outbreak, by disease. We use data from clinicaltrials.gov. We note that a given drug therapy may undergo multiple clinical trials. The beginning of the respective pan/epidemics are December 1, 2019 (COVID-19), April 1, 2015 (Zika), December 1, 2019 (Ebola), and January 1, 2009 (H1N1). COVID-19 therapies measured as of April 22, 2020. The vertical line indicates March 11, 2020.
Table A.6: Planner’s solution versus firm equilibrium when allowing for two consecutive races

<table>
<thead>
<tr>
<th>Number of firms working on:</th>
<th>vaccine project (A)</th>
<th>non-vaccine project (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. $\delta = 0.1$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>81</td>
<td>266</td>
</tr>
<tr>
<td>Firm equilibrium (model predictions)</td>
<td>80.893</td>
<td>266.107</td>
</tr>
<tr>
<td>Planner’s solution (social payoff $= \pi_j$)</td>
<td>83.608</td>
<td>263.392</td>
</tr>
<tr>
<td>Planner’s solution (social payoff $= 2.7 \cdot \pi_j$)</td>
<td>144.513</td>
<td>202.487</td>
</tr>
<tr>
<td><strong>B. $\delta = 0.5$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>81</td>
<td>266</td>
</tr>
<tr>
<td>Firm equilibrium (model predictions)</td>
<td>80.915</td>
<td>266.085</td>
</tr>
<tr>
<td>Planner’s solution (social payoff $= \pi_j$)</td>
<td>83.706</td>
<td>263.294</td>
</tr>
<tr>
<td>Planner’s solution (social payoff $= 2.7 \cdot \pi_j$)</td>
<td>130.693</td>
<td>216.307</td>
</tr>
</tbody>
</table>

Notes: The estimates of the parameters of the model in Panel A are $\hat{\pi}_A = 37.126$, $\sigma_{\text{Non-experienced}} = 3.643$, and $\sigma_{\text{Experienced}} = 1.005$; the in Panel B are $\hat{\pi}_A = 28.072$, $\sigma_{\text{Non-experienced}} = 3.650$, and $\sigma_{\text{Experienced}} = 1.007$. The parameter estimates of the entry rate of firms, the distribution of firm types, and the calibrated parameters are identical to those in Table 5. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the firm equilibrium and planner’s solution are computed based on the average outcomes across 25,000 simulations of the game.

Figure A.2: Number of vaccine and non-vaccine drug therapies predicted by the model and in the data

A) Strategic model

B) Myopic model

Notes: Outcomes for the firm equilibrium are computed based on the average outcomes across 25,000 simulations of the game. The strategic model in panel A corresponds to the model presented in Section 4. The myopic model in panel B corresponds to a version of the model in Section 4 in which each firm behaves as if it is the only firm that has entered and will ever enter the race. The figures restrict attention to the first 100 days of the pandemic.
C Analysis of the Model

Optimal Direction (Lemma 1).


3. The condition $S_A \geq S_B$ can be written as

$$\pi_{1,A} + \pi_{2,B} \geq \pi_{1,B} + \pi_{2,A} + g(M),$$

where $g(M)$ is strictly decreasing and converges to zero as $M \to \infty$, under our assumptions. Note that when $M \to \infty$, $\frac{M\lambda_B}{r+M\lambda_B} \to 1$, so the condition above becomes $\pi_{1,A} + \pi_{2,B} \geq \pi_{1,B} + \pi_{2,A}$.

Efficient Entry in a Crisis (Proposition 1).

1. Consider a crisis of severity $\beta$. Then, the optimal number of firms is

$$\max_{M \in \{0, 1, \ldots\}} V(M)\beta - F(M + 1).$$

Given that $V(M)$ is an increasing function (it is the maximum of two increasing functions), a direct application of Topkis Theorem implies that $M^*$ is weakly increasing in $\beta$.

2. As $\beta \to \infty$, we have that $M^*(\beta) \to \infty$. This implies that $\frac{M^*(\beta)\lambda_B}{r+M^*(\beta)\lambda_B} \to 1$. Simple algebra shows that the condition becomes $\pi_{1,A} + \pi_{2,B} \geq \pi_{1,B} + \pi_{2,A}$.

Equilibrium (Lemma 2).

This result is a direct from Corollary 1 in Bryan and Lemus (2017).

Entry (Proposition 2)

The equilibrium number of firms $M^e$ in a crisis of severity $\beta$ is determined by the condition

$$\Pi^e(M^e) \geq \frac{F}{\beta} > \Pi^e(M^e + 1).$$

Given that $\Pi^e(\cdot)$ is weakly decreasing, the equilibrium number of firms increases with the severity of the crisis.

Inefficient Direction during a Severe Crisis (Proposition 3)
As \( M^e \to \infty \) we have \( P_A \to \pi_{1,A} + \pi_{2,B}, P_B \to \pi_{1,B} + \pi_{2,A}, \Delta(M) \to \frac{\lambda_B - \lambda_A}{\lambda_A} \). Therefore, for \( M^e \) large enough we will have

\[
\lambda_A P_A < \lambda_B P_B - \Delta(M) \lambda_A P_A + M(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A}).
\]

**Excessive Entry (Proposition 4)**

The marginal condition that determine the efficient number of firms to enter (ignoring the integer constraint) is \( G(M) = F \) where

\[
G(M) = \frac{r\lambda_A}{(r + M\lambda_A)^2} \left( \pi_A + \frac{M\lambda_B}{r + M\lambda_B} V_A \right) + \frac{M\lambda_A}{r + M\lambda_A (r + M\lambda_B)^2} V_A.
\]

Denote the solution to this equation \( M^* \), and note that \( G(M) \to 0 \) as \( M \to \infty \).

Suppose that \( M \) firms have entered. In the subsequent game, the firm \( i \) splits its capacity between \( A \) and \( B \) according to \( x_{i,A} \) and \( x_{i,B} \) respectively. Rival firms split their capacity in such a way that there is an aggregate effort towards invention \( j \in \{A,B\} \) (including that of the small firm) is \( z_j \). After the first invention is discovered, the \( M \) firms will direct their capacity towards the remaining invention. Ignoring the integer constraint, the zero profit condition is \( H(M) = F \) where

\[
H(M) = \sum_{j \in \{A,B\}} \frac{x_{i,j} \lambda_A}{r + z_A \lambda_A + z_B \lambda_B} \left( \pi_{1,j} + \frac{M\lambda_{-j}}{r + M\lambda_{-j}} \pi_{2,-j} \right) = F
\]

Denote the solution to this equation \( M^e \). Given that \( x_{i,j} \leq 1 \) and \( z_j \leq M \), we have \( H(M)M \to \Omega \) as \( M \to \infty \), with \( \Omega > 0 \). This shows that, as \( M \to \infty \), there will be a threshold \( M^* \) such that \( H(M) > G(M) \) for all \( M \geq M^* \). As the severity of the crises increases and both \( M^* \) and \( M^e \) are above \( M^* \), we will have \( H(M^e) = F = G(M^*) < H(M^*) \). If we select a type of equilibria with a particular feature (e.g., equilibrium where all firms work on a particular invention), then \( H(\cdot) \) is decreasing, which implies that \( M^e > M^* \).