R&D Competition and the Direction of Innovation*

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February 26, 2022

Abstract

We propose a model to show that when innovation in a given field becomes more lucrative, its *direction* can be distorted even though its *rate* rises. Higher payoffs attract innovators, making the R&D supply side more competitive. This competition endogenously shifts effort toward less promising but quicker-to-invent projects. We empirically quantify the magnitude of this distortion, in the context of pharmaceutical innovation during the Covid-19 pandemic. In the social planner solution, 74 percent more firms would have worked on vaccines and 17 percent more on novel compounds. Policy remedies include advance purchase commitments based on ex-ante value, targeted research subsidies, and antitrust exemptions for joint research ventures.

Keywords: Innovation, direction of innovation, market inefficiency, pharmaceutical innovation

*We thank the editor, Mitsuru Igami, two anonymous referees, participants at the NBER Economics of AI conference, ASSA 2022 Virtual Annual Meeting, as well as seminar participants at Universidad Adolfo Ibañez, Universidad de Chile, University of Arizona, University of Michigan, University of New Hampshire, and University of Pennsylvania (Wharton) for helpful comments. Guillermo Marshall is supported in part by funding from the Social Sciences and Humanities Research Council (Canada). A prior version of this article circulated as "Crisis and the Direction of Innovation".

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1 Introduction

What happens when innovation in a particular field becomes more valuable or less costly? For instance, a demand shock can increase payoffs, as with pharmaceutical innovation during a pandemic. Policy changes like stronger patents, innovation prizes, and research subsidies can make innovation more profitable. A complementary invention may facilitate the development of new ideas, such as machine-learning breakthroughs for drug discovery. The first-order effect of any of these changes in a particular field is to increase the *rate* of innovation.

These exogenous payoff shifters change more than just the rate of R&D, however. While higher payoffs mean firms are willing to pay the fixed cost of setting up a research program, firm entry alters market structure, which endogenously affects the *direction* of invention. That is, the particular research projects firms pursue are a function of the nature of competition. As R&D competition becomes more intense, firms shift effort away from long-run, high-value projects, and toward short-run, less-valuable partial substitutes. Why? Lower-quality, quick-to-discover inventions decrease the ex-post marginal value of high-quality inventions that are partial substitutes. This externality is ignored when firms choose R&D portfolios. In equilibrium, the industry becomes more likely to "race" toward projects that can be completed quickly.

We will first formalize the idea that exogenous shifts in underlying payoffs distort the direction of innovation relative to the socially optimal one, using a simple theoretical model of invention choice with endogenous market structure. We then empirically implement this model to estimate the magnitude of this directional distortion.

Our analysis exploits the extensive and detailed documentation on pharmaceutical development during the Covid-19 pandemic. We use proprietary data on firm characteristics and project choice of entrants during the first six months of the pandemic (i.e., *before* the introduction of major government subsidies and other interventions).[1] This setting is ideal for four reasons. First, there is well-documented data on hundreds of entrants working on Covid-19 projects. Second, there are well-defined choices of direction such as "vaccine or therapeutic," with vaccines widely believed ex-ante to be more difficult to develop and more socially valuable (see, e.g., Xue and Ouellette, 2020). Third, there is standardized data on each firm's prior research capabilities. Fourth, we know exactly when the crisis started, and

[1] Beginning in late May 2020, governments introduced large vaccine-directed subsidies, such as Operation Warp Speed in the United States. Such public interventions are likely to dominate (or at least confound) the market-structure effect that this paper highlights. Thus, we exclusively focus on the first six months of the pandemic.

we observe a shock to its severity in early March 2020 when the epidemic globalized.

In the social planner solution, our estimates show that 74 percent more firms would have worked on vaccines and 17 percent more on novel compounds between January and June 2020. Of the 74 percent gap, 10.2 percent remains even if we assume pharmaceutical firms earned the full social surplus of their inventions: strategic racing rather than just underappropriation slowed vaccine development.

Our results principally build on two strands of the innovation literature, one theoretical and one empirical. On the theoretical side, the potential for strategic racing either in terms of the quantity of R&D (Loury (1979); Reinganum (1982)) or its direction (Bryan and Lemus (2017); Hopenhayn and Squintani (2021)) has long been noted. This literature broadly shares the idea that innovators do not account for how their research effort affects the probability of success by other firms. We extend this insight by endogenizing market structure, showing that since the extent of strategic racing is increasing in R&D market fragmentation, "hot" technological areas that attract many entrants are more at risk of directional distortion.

There is a nascent empirical industrial organization literature of market structure on innovation outcomes (Goettler and Gordon (2011), Igami and Uetake (2020)). This literature, however, does not speak to the direction of innovation. In non-structural work on invention direction, Moser (2005) suggests that inventors in countries without strong patent protection shift effort toward inventions which can be protected by secrecy, such as Swiss watches. Acemoglu et al. (2012) shows that factor scarcity and inventor subsidies affect the direction of invention in the context of climate change policy. Hanlon (2015) does the same when studying textile innovation at the time of the Civil War. These studies demonstrate that R&D direction shifts to areas where inventor rewards are higher and reacts to changes in factor prices and technological substitutability. However, to our knowledge there are no other empirical studies on distorted invention direction based on endogenous market structure, structural or otherwise.

Finally, there has been a great deal of research using the Covid-19 pandemic as a case for innovation policy. This literature is vast; however, of particular note are Gross and Sampat (2021) on how Covid-19 policy compares, favorably or otherwise, to World War II "crisis" innovation, Agarwal and Gaule (2021) showing that the quantity of scientific research can in some cases be quite elastic, without crowd-out, when sufficient public spending is directed toward a particular goal, and Kremer et al. (2022) on incentivizing vaccine production with advanced market commitments.

2 A Model of Directional Inefficiency

Consider the following simple framework to analyze the impact of an *exogenous payoff shifter*. A payoff shifter is any exogenous change that scales up the payoff, or scales down the fixed R&D costs, of innovations in a particular field. For example, a demand or technology shock may increase the payoffs of all inventions, or a new regulatory policy may make it less burdensome for firms to enter. This exogenous payoff shifter induces entry, which exacerbates R&D competition among inventors. They therefore face more incentive to "race" toward easier and lower-value research, even when doing so is socially inefficient. Because the value of inventions ex-post depends on what substitutes exist, these low-value inventions decrease the payoff inventors working on more difficult projects with higher ex-ante value will earn.

Projects: There are two partially-substitute projects, $j \in \{A, B\}$, characterized by three project-specific parameters: (1) the ease of invention λ_j; (2) the lump-sum expected payoff $\pi_{1,j}$ to the inventing firm when nothing has been invented yet; and (3) the lump-sum expected payoff $\pi_{2,j}$ to the firm that invents j if the other project has already been invented. This captures the notion that the payoff of each project depends on the *history* of discoveries. For example, let the expected value of a vaccine A be 10 and of a treatment drug B be 6 when nothing has been invented yet. Once either has been invented, let the marginal value of the other invention fall in half. For instance, 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 5 since effective therapeutics will lead only high-risk populations to vaccinate. In this case, $\pi_{1,A} = 10$, $\pi_{1,B} = 6$, $\pi_{2,A} = 5$, and $\pi_{2,B} = 3$. Note that inventing A first and B second is socially optimal: the social payoff is 13 instead of 11. For exposition, we present our results with lump-sum payoffs, interpreted as an infinitely long patent on a narrow invention. In Online Appendix G, we relax this assumption in the case of flow payoffs that are interrupted by new discoveries. The primary qualitative insights are unchanged.

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. Each firm that enters 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.[2] 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, both at the individual firm level and in the aggregate. The game ends after the two inventions have been discovered.

Exogenous Payoff Shifter: An exogenous innovation shifter scales all payoffs up or reduces the fixed cost of entry, i.e., the ratio $\frac{\pi_{t,i}}{F}$ increases by a factor of $\eta > 1$.[3]

We make three additional assumptions to clarify precisely the nature of directional distortions. First, we assume that the payoff of any invention equals its social surplus. In equilibrium, scaling this payoff up or down will only affect direction choice to the extent that it changes the total number of firms that enter. To emphasize the nature of directional distortions rather than underappropriation we, therefore, assume that firms fully capture the social value of their inventions.[4] 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, $\pi_{1,A} > \pi_{1,B}$ and $\lambda_B > \lambda_A$. Moreover, we assume that A and B are partial substitutes and inventing A first is the socially optimal discovery path, that is, $\pi_{1,A} + \pi_{2,B} > \pi_{1,B} + \pi_{2,A}$.[5] For instance, A may be a vaccine and B a therapeutic during an epidemic. 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 would be so low that no firm would ever work on it in equilibrium, regardless of discount rate or market structure.

[2] Note that once A has been invented, B is the only possible project, and vice versa.

[3] In practice, the shift in payoffs may not be uniform and could be time dependent. We abstract away from these cases because we are interested in changes in the direction of innovation caused by the endogenous change in market structure rather than an exogenous change in the relative value of the inventions.

[4] Alternatively, this can be interpreted as saying that we show the extent of directional distortion *even if* payoffs are high enough that inventors completely appropriate the expected value of their inventions.

[5] We do not directly model the dynamic demand system. However, for the sake of intuition, consider two cases which generate this pattern. First, let entry of the second project be completely unprofitable after the first invention induces the existence of complements, regulatory barriers or network effects. Then we have that $\pi_{2,B} = \pi_{2,A} = 0$ and our condition simplifies to $\pi_{1,A} > \pi_{1,B}$. Alternatively, there may be a potential invention in a related industry using the same researchers and capital, which has an expected flow payoff of π_C. If the ex-post marginal expected flow payoff of the second project falls below π_C, firms will no longer pursue it.

2.1 Planner Optimum

Consider first the efficient allocation of research across projects by a fixed set of N firms. 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

$$V_j^S = \int_0^\infty \pi_{2,k} \cdot N\lambda_k e^{-N\lambda_k t} \cdot e^{-rt} dt = \frac{N\lambda_k}{r + N\lambda_k} \pi_{2,k} \tag{1}$$

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

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

subject to $x_A + x_B = N$ and $x_j \geq 0$, for $j \in \{A, B\}$. The probability that no innovation has arrived before time t is $e^{-(\lambda_A x_A + \lambda_B x_B)t}$, and the rate at which project k is invented is $\lambda_k x_k$. In the following lemmas and propositions, all proofs are left to Online Appendix F.

Lemma 1. *The planner optimally allocates all researchers to project A first and then to project B if and only if:*[6]

$$\lambda_A P_A \geq \lambda_B P_B - \frac{N(\lambda_B - \lambda_A)}{r + N\lambda_A} \lambda_A P_A. \tag{2}$$

As N grows arbitrary large, Equation (2) becomes $\pi_{1,A} + \pi_{2,B} \geq \pi_{1,B} + \pi_{2,A}$. That is, for sufficiently high N, the optimal first project is the more difficult, long-term project A. Why? Though the future is discounted, when the number of firms performing R&D is high enough, both projects can be finished arbitrarily quickly. Therefore, a planner wants firms to work on the highest value inventions ignoring their difficulty.

Let us now endogenize entry. Denote by $V(N)$ the social payoff under the efficient research

[6] 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.

direction with N firms. The optimal number of active firms, denoted by N^*, solves

$$\max_{N\in\{0,1,2,\ldots\}} V(N) - F \cdot N$$

It is straightforward to show that $V(N)$ is a homogeneous function in scaling all payoffs π by a constant factor. Therefore, scaling all payoffs π (e.g., shock in demand that makes all inventions more valuable) or reducing entry costs F (e.g., a reduction in regulatory burdens) has the same effect on the optimal number of firms.

Proposition 1. *We have:*

1. *An exogenous payoff shifter makes it socially optimal to increase the number of firms.*
2. *When the exogenous payoff shift is intense (η is sufficiently large), it is optimal to allocate firms toward the long-term project.*

Proposition 1 is intuitive. Shocks that scale payoffs or reduce entry costs affect the direction of invention only *indirectly* through the number of firms. For instance, during a pandemic it is worthwhile for the planner to pay the fixed entry cost for more firms. As we noted above, when the number of firms who enter is sufficiently high, any project can be invented arbitrarily quickly, hence the planner optimally directs firms to work on high-value projects even when they are difficult.

2.2 Equilibrium Allocation of Firms to Projects

In this section, we study the equilibrium allocation of firms to projects (henceforth "equilibrium"). In contrast to the social planner, the expected private continuation payoff after the first invention is

$$V_j = \frac{1}{N} V_j^S$$

That is, following the first successful invention, all firms can work on the remaining invention and each firm is equally likely to invent it.

Let $a_{-ij} = \sum_{k\neq i} x_{kj}$ be the cumulative effort by firms other than i on project j, and let $\tilde{P}_j = \pi_{1,j} + V_j$. The best response of firm i solves

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

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 $e^{-(\lambda_A(a_{-iA}+x_{iA})+\lambda_B(a_{-iB}+x_{iB}))\cdot t}$, 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.

Lemma 2. *Suppose that the efficient research direction is project A when N firms have entered. There exists an equilibrium where all firms work on A if and only if*

$$\lambda_A P_A \geq \lambda_B P_B - \frac{N(\lambda_B - \lambda_A)}{r + N\lambda_A}\lambda_A P_A + (N-1)(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A}). \tag{3}$$

The condition that guarantees that A is the efficient direction is distorted by a *strategic racing externality*, captured by the term $(N-1)(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A})$. The strategic racing externality is proportional to the difference of immediate flow payoffs and strictly increasing in the number of firms. 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. Intuitively, this is similar to business stealing from entrants with fixed costs, with the added dimension that more "business," as measured by the fraction of total surplus earned, can be stolen by deviating toward quick projects. Thus, even if the *level* of R&D is efficient, in equilibrium firms may deploy their research in an inefficient direction.

This externality has a particularly worrying consequence when invention in a given field becomes more lucrative:

Proposition 2. *We have:*

1. *An exogenous payoff shifter weakly increases the number of firms in a symmetric equilibrium.*
2. *When the innovation shift is intense (η is sufficiently large), all firms working on the efficient, long-term project is not an equilibrium.*

Again, scaling payoffs or reducing entry costs changes directional choices only through the number of firms. If the number of firms were held constant, the fact that *all* inventions in a given area see their payoffs increase by the same factor means that the optimal (or equilibrium) choice of which project to work on does not change. However, when we allow entry to be endogenous, these higher payoffs mean more firms can enter and still cover the fixed cost of performing R&D. More entry for the planner means all inventions come

relatively quickly, hence it is not worth sacrificing high-value inventions for low-value but quick ones. The opposite is true in the market equilibrium. More entry means that each firm cares more about the payoff they can get from being the first to invent something, and less about anything invented after the first for which a given firm accrues only $\frac{1}{N}$ of the payoff in expectation.[7]

Summing up, higher payoffs mean more firms enter in equilibrium, which means everything can be invented quicker, so it would be socially optimal to work on the highest value projects. From each firm's perspective, however, competing against more firms increases the incentive to work on quick, low-value projects by making it relatively more important to be "first" rather than "best".[8]

Finally, is there too much or too little entry overall? 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, when firms independently choose whether to enter, they do not account for how their entry lowers the profits captured by other firms. This is a negative externality, so the market solution will tend to over-supply firms.

Proposition 3. *A sufficiently large payoff shifter causes over-entry relative to the efficient 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). With large payoffs or low entry costs, 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. Combining these propositions, with free entry and payoffs equal to the social value of any invention, there will be excessive entry and the firms that enter will work on inefficiently short-term projects. Even if we manage to get the rate of entry to the optimal level, the firms that enter have too much incentive to work on short-term, low-value projects.

[7] Part 2 in Proposition 2 holds even if the firms only appropriate a fraction of the social surplus. Conditional on the number of competitors, firm choices are unaffected when payoffs are scaled down, but the equilibrium number of firms that enter decreases. A large increase in the payoff to all projects will distort directional choices, even after accounting for fewer firms entering in equilibrium due to imperfect appropriation.

[8] 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. The 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, 84 percent of Covid-19 projects were wholly private or partially sponsored by the private sector.

2.3 Policy Interventions

If the equilibrium firm allocation is inefficient, what can be done? The theoretical solution is straightforward: increase the payoff of the long-run project relative to the short-run project, or reduce strategic racing behavior by permitting research joint ventures and similar collaborative regimes. This is standard Pigouvian economics, where we can fix an inefficiency either with taxes and subsidies, or by directly removing the externality. 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 to invention, it induces more entry and makes directional distortion worse. The same is true of generic rather than targeted research subsidies. The fundamental problem is that the government needs to simultaneously induce entry *and* prevent the firms that enter from deviating to quick, low-value projects.

Three common policies achieve this result in the context of the stylized model above. First, research joint ventures on projects that are expected to be harder to invent than most inventions in a sector ought to be encouraged.[9]

Second, targeted subsidies, incentivizing only difficult, high-value inventions, while permitting unsubsidized research on other projects, simultaneously induce entry while avoiding a directional distortion. While in some cases targeted subsidies can be seen as the government "picking winners," the nature of socially-valuable inventions is often widely known.[10]

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. If the probability of finishing a vaccine first is quite low, and the ex-post expected profit of a vaccine does not exceed that outside option, firms will deviate to working on the drug and the vaccine will not be invented. An AMC

[9] See Grossman and Shapiro (1986) for a deeper analysis of the antitrust issues with research collaborations. In April 2020, Sanofi and GlaxoSmithKline, normally rivals, formed a joint research venture to develop a Covid-19 vaccine. See https://www.gsk.com/en-gb/media/press-releases/sanofi-and-gsk-to-join-forces-in-unprecedented-vaccine-collaboration-to-fight-covid-19/ for details

[10] We use data only through the first six months of the pandemic because targeted subsidies toward vaccines became a major part of the policymaker arsenal with the announcement of "Operation Warp Speed" subsidies. The May 4th, 2020 issue of the New York Times discussed existing large subsidy programs for Covid-19 inventions, noting that they were targeted broadly at "diagnostics, therapeutics, and treatments" rather than vaccines (Athey et al., 2020).

committing to pay the *ex-ante* social value of an invention, even if future inventions lower their value, can completely remedy directional inefficiency. Contemporaneous estimates of the value of targeted Covid-19 vaccine AMCs argued 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).

3 Measuring the Magnitude of Directional Inefficiency

Given the theoretical distortion identified in the previous section, we are interested in two empirical questions. First, when can we identify the key primitives that drive project choice (i.e., expected payoffs and entry costs) from observed R&D data? Second, what is the magnitude of competition-driven inefficiency in the direction of invention? Consider the case of pharmaceutical research during the Covid-19 pandemic. We will begin by showing a series of stylized facts about the small fraction of Covid-19 research devoted to vaccines, particularly after the pandemic becomes more severe. We will then discuss how to estimate an empirical model of R&D decisions capturing the possibility of strategic racing, and use that model to investigate Covid-19 R&D racing empirically.

3.1 Descriptive Evidence from Covid-19 Pipelines

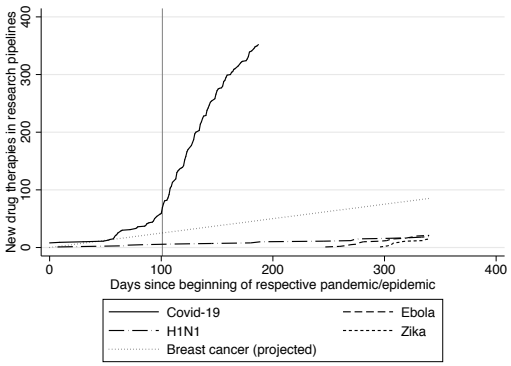
Before estimating entry into Covid-19 research structurally, we present descriptive evidence on the Covid-19 innovation race. We use proprietary data from "BioMedTracker," a dataset produced by Informa PLC, which tracks the development history of pharmaceutical drug projects. For every pharmaceutical 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.[11] See Online Appendix Section A for details about the data construction.[12]

Figure 1 (Panel A) shows that the rate of Covid-19 therapies in research pipelines exceed that

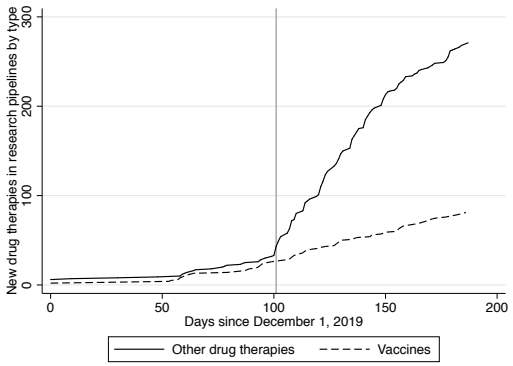
[11] We complement these data with information from public sources, such as recent viral epidemics.

[12] 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 Covid-19 drug therapies in research pipelines, by drug classification .



A) Therapy Pipelines



B) Covid-19 therapies, by drug classification

Notes: Panel A: The figure plots the number of drug therapies (at all stages of development) in research pipelines, by disease. The beginning of the respective pan/epidemics are December 1, 2019 (Covid-19), April 1, 2015 (Zika), December 16, 2013 (Ebola), and January 1, 2009 (H1N1). Covid-19 therapies measured as of June 15, 2020. The projected number of breast cancer drug therapies are provided as a reference and are computed using the formula entry-rate*time, where 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. Panel B: The figure plots the number of Covid-19 drug therapies (at all stages of development) in research pipelines, by type of drug.

of Ebola, Zika, H1N1, and even breast cancer by at least an order of magnitude.[13] Forty-one of these drug therapies were already undergoing clinical trials as of June 15, 2020 (8 were 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.[14] The figure also shows 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.[15]

Though the rate of Covid-19 entry is very high, especially after mid-March, the type of entry

[13]Cancer in general received more NIH funding than any other disease category (NIH, 2020), and breast 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).

[14]See footnotes 1 and 10 as a justification for choosing June 2020 as the cutoff date.

[15]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.

Table 1: Entrant characteristics, by repurposed/not repurposed and entry time

	Not Repurposed	Repurposed	Diff.	Before March 11	After March 11	Diff.
Vaccine	.448	.017	-.431	.464	.186	-.278
			[0]			[0]
Repurposed	0	1	1	.357	.534	.177
			-			[.015]
Establishment year	2009.557	2005.506	-4.052	2005.571	2007.875	2.304
			[.001]			[.152]
Pipeline size	50.247	67.258	17.011	84.143	54.064	-30.079
			[.284]			[.221]
Experience w/ vaccines	.496	.096	-.401	.5	.222	-.278
			[0]			[0]
Experience w/ antivirals	.593	.32	-.272	.731	.379	-.351
			[0]			[0]
Experience w/ infectious diseases	.696	.41	-.286	.75	.49	-.26
			[0]			[0]

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.

shows striking patterns. Figure 1 (Panel B) shows entry by drug classification over time. The figure shows a trend away from vaccines after the perceived severity of the pandemic increases in early March. Along these lines, Online Appendix Figure B.1 shows a trend towards repurposed drugs starting in early March.[16] In particular, the share of vaccines among all drug therapies is 46 percent prior to March 11, and 19 percent following the pandemic declaration. Likewise, the share of non-repurposed drugs is 64 percent prior to March 11 and 47 percent thereafter. That is, the rate of entry of vaccines is essentially constant before and after the globalization of the pandemic in mid-March, while the rate of entry of non-vaccines, especially repurposed drugs, increased dramatically.

Can firm experience explain these patterns? Table 1 shows that post-March 11, Covid-19 entrants have less experience with vaccines, antivirals, and with infectious diseases, and have a smaller pipeline, though they are not wholly inexperienced. 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.

[16] Repurposed drugs are defined as those which existed prior to the beginning of the relevant outbreak and which have multiple indications.

To examine whether a particular type of firm was driving the change in the direction of innovation after March 11th, we use a logistic regression to uncover the relationship between project choice and firm characteristics, controlling for whether the firm entered before or after March 11th. Table 2 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 the full sample of Covid-19 entrants (Table 2, Column 1), but also true for the subset of experienced firms that were plausibly capable of developing a Covid-19 vaccine (Table 2, Column 2).[17] 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.[18]

These facts are consistent with the theory in Section 2. Higher payoffs attract entry from firms that would otherwise not find the fixed cost of R&D worth paying. These firms expect lots of competition in drug development, especially after the pandemic increases in severity. Therefore, on the margin effort shifts toward lower-value, quicker projects.

3.2 Empirical model

In order to quantitatively match real-world data, we extend the theoretical model in three ways. First, we will assume that firms enter sequentially rather than simultaneously at the beginning of the game. Second, we allow for different firm types which are defined by firm-specific prior research experience. Third, we allow the cost of working on a project to be both type- and project-specific, rather than identical for all firms and projects as in Section 2. This introduces heterogeneity in research capacity, making some firms better at research than others, but it also allows for project-specific heterogeneity (i.e., a given project may be more costly for some firms even conditional on research experience).

The exogenous payoff shifter that we consider is the global pandemic declaration of Covid-

[17] Specifically, we define a firm to be experienced if it has had a vaccine project and a drug project for an infectious disease prior to Covid-19 in their research pipelines. Online Appendix Table B.1 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.

[18] Online Appendix Figure B.2 shows public funding pledges over time for vaccine and non-vaccine projects. The figure shows that by the end of our sample period, vaccine and non-vaccine projects had received an equal amount of public funding, which suggests that public funding is unlikely to have been behind the shift away from vaccines after March 11. If anything, the figure shows that public funding for vaccine projects accelerated after March 11, which should have at least partially counteracted the "racing distortion."

Table 2: Project choice among Covid-19 entrants: Logit regressions

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

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.

19.[19] 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 or project B. In our application, project A is the vaccine and project B is a non-vaccine drug therapy.

The cost of pursuing project j for a firm of type θ is $c_j(\theta)$, which is a privately-observed random variable. As in Section 2, this is a one-time cost paid by the firm at the time of entering the competition.[20] We assume that no more than $\bar{N}$ firms can enter per project.[21]

[19] In the context of our model, the increase in the entry rate after March 11 can be explained by a change in expected payoffs relative to costs of inventing a drug. See also footnote 15.

[20] Alternatively, we could have put the heterogeneity in the probability of success. For empirical tractability we choose to capture all firm heterogeneity in their project-specific entry costs.

[21] In the Covid-19 estimation, we assume $\bar{N} = 300$ per project, which combined equals 1.5 times the 99th percentile in the distribution of number of drug projects per disease. That is, we assume that up to 600 firms can enter the innovation race.

Once the first invention occurs, we assume no further entry occurs, and in our most general model we allow that each firm earns a continuation value which depends on which project they pursued. This implicitly allows the model to capture settings where subsequent inventions of any type are valuable, and where follow-on inventions of the type which was not invented first retain some value. However, in our baseline model, we assume that the innovation race ends when either one of the two initial projects is invented.

When a firm enters, the relevant state variables are the number of firms pursuing each project, (n_A, n_B). Calendar time is irrelevant since invention probabilities for each firm have Poisson arrival rates. 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

$$V^j_{n_A,n_B} = \frac{\lambda_j \pi_j + \mu\Big(E_\theta[\Pr(A|\theta, n_A, n_B)]V^j_{n_A+1,n_B} + E_\theta[\Pr(B|\theta, n_A, n_B)]V^j_{n_A,n_B+1}\Big)}{r + n_A\lambda_A + n_B\lambda_B + \mu}. \quad (4)$$

In Equation 4, a firm working on project j wins the race with flow probability λ_j, in which case it receives a payoff of π_j.[22] For notational ease, the equation omits the continuation values after the first innovation has been invented. With flow probability μ a new firm enters the race before a discovery has been made. This new firm, depending on its type and resulting project-specific entry costs, will choose between A or B. If the new firm chooses $j \in \{A, B\}$, the game will transition to the state $(n_j + 1, n_{-j})$.

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

$$V^A_{n_A+1,n_B} - c_A(\theta) > V^B_{n_A,n_B+1} - c_B(\theta). \quad (5)$$

The type-specific cumulative distribution function of the cost differences $c_A(\theta) - c_B(\theta)$ is F_θ, which depends on a shape parameter, $\sigma(\theta)$. Thus, the entrant chooses to pursue project A with probability $\Pr(A|\theta, n_A, n_B) = F_\theta(V^A_{n_A+1,n_B} - V^B_{n_A,n_B+1})$.

Because we limit the total number of firms that can pursue each project, and firms enter at rate μ, for T large enough, almost certainly all the firms have entered provided that no project has been invented. We can analytically compute the payoff of a firm working on

[22] In our setting, a firm's chance of success is independent of the time the firm has been in the race, conditional on no success. Doraszelski (2003), for instance, study the impact of learning and investment on R&D races. We do not have data on investments, so we do not model this dimension.

project j at this time T, and use these payoffs to solve the game by backward induction.[23] We find the unique equilibrium of the game using this recursive procedure.

3.3 Calibration and Estimation

Let us now clarify why certain parameters have their values imposed and why others can be estimated based on variation in the panel data of pharmaceutical entry.

Parameters. In our application, we assume two projects: a vaccine project (A) and a non-vaccine project (B). We also assume an unexpected exogenous payoff shifter with a date that is known to the researcher. As discussed in Section 2, the exogenous payoff shifter leads to more entry in equilibrium. We will permit the arrival rate of both types of firms to vary as a function of the severity shock.

As a result, we have the following set of parameters (summarized in Table 3): the project difficulties λ_A and λ_B, the discount rate r, the fixed cost variance parameters $\sigma(\theta)$ for every $\theta \in \Theta$, the payoffs π_A and π_B, the continuation values following the first invention for each firm working on a given project $\pi_{2,A}$ and $\pi_{2,B}$, the arrival rates of all firms in both periods μ_{t_1} and μ_{t_2}, and the fraction of firms of type θ in each time period κ_{θ,t_1} and κ_{θ,t_2}.[24]

In our application, 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. With two types, we simply denote by κ_t the fraction of firms of experienced firms in time period t.

Normalizations. We first normalize scale by setting $\pi_B = 1$. Hence, the payoff π_A and the cost parameters will be normalized relative to the value of the short-term invention. In our baseline model, we set the continuation values $\pi_{2,A}$ and $\pi_{2,B}$ to zero. We also estimate an alternative specification where these values are a function of π_A and π_B (e.g., when the second invention in a given class is worth half the value of the first invention). In that specification, the discount rate, the arrival rates, and the estimated value π_A fully determine $\pi_{2,A}$ and $\pi_{2,B}$.

Arrival rates. Without observing the payoff of realized inventions, it is impossible to

[23] When no further entrants can enter the innovation race, the payoff of pursuing project j is given by $V^j_{\bar{N},\bar{N}} = \lambda_j \pi_j / (r + \bar{N}(\lambda_A + \lambda_B))$.

[24] More generally, the model can be extended to K innovations. Identification of the primitives requires every innovation to be chosen by at least one firm. All other identification arguments remain the same.

Description	Parameter	Method
Project difficulty	λ_A, λ_B	calibrated
Project payoffs	π_A, π_B	estimated
Continuation Values	$\pi_{2,A}$ and $\pi_{2,B}$	calibrated
Arrival rates	μ_{t_1} and μ_{t_2}	estimated
Fraction of experienced firms in time t	κ_t	estimated
Discount rate	r	calibrated
Cost variance	$\sigma(\theta)$ for every $\theta \in \Theta$	estimated

Table 3: Model parameters

separately identify λ_j and π_j. Intuitively, firms may enter slowly because the inventions' payoffs are low, or because it will take a long time to invent, and hence the payoffs will be heavily discounted. Observing the ex-post time until invention is only possible for those that are invented. Even there, we do not want to conflate an invention that was found quickly by good luck with the inventor's ex-ante belief that it would be easy to invent. At the beginning of an innovation race, historical data is all the information firms have to form their beliefs about the λ_j of each project. Therefore, we choose λ_A and λ_B to match historical normal rates of development of an invention of a given type being developed by a single firm.

We set the values of the arrival rates to the estimated historical approval times for infectious diseases, $\lambda_A = 5.55 \times 10^{-5}$ (vaccine project), $\lambda_B = 7.607 \times 10^{-5}$ (non-vaccine project), reflecting that vaccines have historically taken longer to develop (Lurie et al., 2020).[25]

We set the annual discount rate to be 10 percent, equivalent to a daily discount rate $r = 2.61 \times 10^{-4}$.

Estimated Parameters. 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 inventions. Similarly, we allow for an exogenous change in the composition of potential entrants to reflect that fewer experienced firms entered after March 11.[26] Also, we assume that the cumulative distribution function of the difference in project-specific entry costs $c_A(\theta) - c_B(\theta)$ is given by $F_\theta(t) = ((t+1)/2)^{\sigma(\theta)}$ with $\sigma(\theta) > 0$

[25]Specifically, to compute λ_A and λ_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. Given the empirical rate of entry into Covid-19 research, these arrival rates imply a 95 percent chance of a successful therapeutic and vaccine after 250 and 700 days of research, respectively. Empirically, the first Covid vaccine which reported Stage 3 results in preparation for regulatory filing was Pfizer/BioNTech on November 9, 2020, 343 days after the pandemic began.

[26]That is, we do not model why different types of firms enter, but instead model their project choice conditional on entering.

and $t \in [-1, 1]$ (i.e., cost differences cannot be greater than π_B in absolute value), and we estimate the parameters $\sigma(\theta)$ for each type.[27]

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 the likelihood function, we make use of Equation 5 to determine the probability that a firm of type θ 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 explicit formula for the likelihood function is in Appendix C.

We leverage revealed preference to identify the payoff of project A, π_A, which in our empirical application is the slow-to-invent vaccine project. 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 that can rationalize these choices is π_A. 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, 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.

Critical Assumptions. A number of modeling assumptions play a fundamental role in allowing us to back out welfare-relevant parameters from observed firm behavior. In particular, in our baseline results, we require that 1) heterogeneity is limited to *project-specific costs*, 2) payoffs by invention are *scaled proportionally*, 3) all inventors are *for-profit*, 4) entry opportunities *arrive stochastically*, 5) the value of the alternative invention *falls to zero once its partial substitute is invented*, and 6) the difficulty of vaccine and therapeutic Covid projects is ex-ante expected to be *similar to historical drug discovery of each class*. Of course, each of these abstractions is counterfactual, and hence the empirical estimates must be interpreted with caution. We perform robustness checks relaxing these assumptions.

[27] The expected cost difference of a firm of type θ is given by $(\sigma(\theta)-1)/(1+\sigma(\theta))$. This distribution bounds the cost differences to be between -1 and 1.

4 Results

4.1 Parameter Estimates and Fit

Table 4 gives parameters from the structural model. The estimated ex-ante expected value of a vaccine is 40.6 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 firms dropped to 18.8 percent afterwards. The expected cost difference between the vaccine and non-vaccine projects is 0.57 and 0 (i.e., the expected cost difference of type θ is given by $(\sigma_\theta - 1)/(1 + \sigma_\theta)$), respectively, for non-experienced and experienced firms.[28]

To gauge model fit, Figure 2 plots the raw data versus the number of vaccine and non-vaccine projects over time predicted by the model. The figure shows the average number of vaccine and non-vaccines, over 25,000 simulations of the model using the estimated parameters, matches closely the number of firms in each project at every moment in time. The first two rows of Table 5 also show that the model accurately predicts the share of firms of each type that are working on vaccines and drug therapies.

4.2 Counterfactual Simulations

Planner's Solution. We measure the extent of directional efficiency by solving for the socially efficient allocation of firms across projects. Here, the social planner controls the allocation of each entrant to either vaccines or non-vaccines, but not the rate of entry of firms. In our baseline case, when computing the planner's solution we assume that the social surplus of invention j is a multiplicative increase above the firm's expected profit. In particular, we use the rough estimate in Kremer (1998) that, if willingness to pay for medical treatments is proportional to income, the social surplus is 2.7x the fixed-price revenue of a monopolist inventor.[29] Again, we run 25,000 simulations of the social planner's problem and

[28] 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 therapeutic. 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. In Online Appendix E, we show the ex-post value of positive news about vaccine trials for each of the three Western vaccines whose Stage 3 trial finished in 2020.

[29] This estimate comes from assuming that willingness to pay for medical treatment is proportional to

Table 4: MLE estimates of the parameters of the model

Parameter	Estimate	St. Error
π_A	40.636	15.345
π_B (normalized)	1	-
$\mu_{\text{Before March 11}}$	0.550	0.074
$\mu_{\text{After March 11}}$	3.382	0.198
$\sigma_{\text{Non-experienced}}$	3.648	0.415
$\sigma_{\text{Experienced}}$	1.007	0.209
$\kappa_{\text{Before March 11}}$	0.446	0.066
$\kappa_{\text{After March 11}}$	0.188	0.023
N	347	
$\sum_j l_j(\hat{\delta})/N$	-0.516	

Notes: Standard errors computed based on the asymptotic distribution of the MLE estimator. Calibrated parameters: $\lambda_A = 5.55 \times 10^{-5}$, $\lambda_B = 7.607 \times 10^{-5}$, and $r = 2.61 \times 10^{-4}$ (time is measured in days).

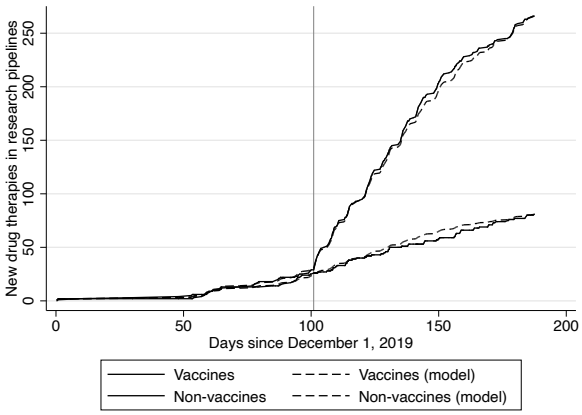
compute the outcomes for each simulation.

Role of Appropriability and Beliefs. We compute the equilibrium allocation of firms in counterfactual scenarios. We first assume that firms earn the full social surplus of their inventions. Second, we assume both that the full social surplus is earned and that firms all believe future R&D competition will be stronger or weaker than what was actually observed. In particular, in the "low competition" scenario, we recompute the equilibrium under the assumption that firms believe rival entry in the future would have remained at pre-March 11 levels throughout the game, while keeping actual entry fixed and still allowing for the composition of firms to change after March 11. In this counterfactual scenario, firms are making their choices with the same state variables as in the observed equilibrium, and the same cost structure; only their belief about future competition is altered. This results in firms facing less competitive pressure when making their project choices. Alternatively, in the "high competition" scenario, it is the pre-March 11 entrants who believe that they will face future entry at the rapid rate that occurred in the observed data only after the March shock to pandemic severity. By comparing the observed equilibria with counterfactual equilibria, we are able to quantify how these factors affect directional distortion.

Table 5 compares the simulation-average planner solution to the expected outcomes in equilibrium. In the baseline case, in line with observed data (A.1), the equilibrium allocation involves 80.8 firms working on a vaccine project (A.2). However, 140.5 firms would be as-

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.

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



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

signed by the planner to do so (B.2). The planner assigns many firms to work on a vaccine even though many are inexperienced and are estimated to have much higher costs to working on a vaccine rather than a therapeutic. Comparing A.2 and B.2, the gap between the planner optimum and the market equilibrium is largely driven by the fact that firms bear the full cost of drug development but only earn a fraction of the social surplus of their invention.

A natural remedy, therefore, is to ensure firms earn the full ex-ante social surplus of their inventions. Table 5 C.1 shows that, under that payoff assumption, 134.3 firms would work on vaccines in equilibrium. 10.4 percent of the firms who deviated from the social planner optimum, or 6.2 firms overall, remain deviating even when payoffs are scaled up to match social surplus. This remaining difference is due to the strategic incentive to deviate away from more difficult projects.[30] Examining the right-most columns, the gap between the planner optimum and equilibrium project choice when payoffs are scaled up is driven by both experienced and non-experienced firms.

Table 5 C.2 and C.3 show the importance of beliefs about competition. C.2 shows that had firms always believed competition would remain limited to its pre-March 11 level, many more late entrants would have worked on vaccines: indeed, there would be over-entry, especially from less experienced firms. C.3 considers the counterfactual where all firms believe that the

[30]Note that we argued in Section 3 that a scaling of the payoff parameters did not affect directional choices *directly*. This was driven by the assumption that entry costs are the same for both projects. In the empirical model, however, we allow for cost heterogeneity across projects, which implies that if we scale payoffs keeping costs fixed, directional choices are affected directly.

Table 5: Planner's solution versus equilibrium allocation of firms

	Number of firms working on:		Share of firms working on vaccines (A):		
	Vaccine (A)	Non-vaccine (B)	Experts	Non-experts	Overall
A. Data and model predictions					
1. Data	81	266	0.588	0.127	0.233
2. Market equilibrium (model predictions)	80.812	266.188	0.587	0.127	0.233
B. Planner's solution					
1. Social payoff$_j = \pi_j$	81.473	265.527	0.592	0.128	0.235
2. Social payoff$_j = 2.7\pi_j$ (baseline case)	140.449	206.551	0.756	0.299	0.405
C. Counterfactual Market Equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	134.347	212.653	0.744	0.280	0.387
2. Fixed at pre-March 11 levels	166.156	180.844	0.797	0.383	0.479
3. Fixed at post-March 11 levels	107.885	239.115	0.661	0.206	0.311

Notes: Outcomes are measured at 188 days since December 1, 2019. Outcomes for the equilibrium allocation and planner's solution are computed averaging outcomes across 25,000 model simulations. Counterfactual C.1 considers the case when the inventor of project j earns 2.7x the estimated payoff of project j. Counterfactual C.2 considers the case where all firms entering after March 11 believe that future entry will be at the pre-March 11 rate, and that the inventor of project j earns 2.7x the estimated payoff of project j. Counterfactual C.3 considers the case where all firms entering before March 11 believe that future entry will be at the post-March 11 rate, and that the inventor of project j earns 2.7x the estimated payoff of project j.

entry rate of R&D competition is as high as it was post-March 11, when we estimate around 3 firms enter the race each day. Here, only 107.9 firms work on vaccines, 33 fewer than the social optimum. The March 11 demand shock occurred after many experienced firms had already begun working on Covid R&D, under the expectation of more limited competition. It was therefore fortunate that the most experienced vaccine inventors had largely entered before March 11, as our estimates suggest many of these firms would have deviated to working on therapeutics had they known how much competition they would face.

Government Interventions. We use 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 optimal balance of vaccines and non-vaccines given estimated firm capabilities?[31] 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 of 0.3 percent of the value of the non-vaccine project ($\pi_B = 1$) would induce optimal direction choice if the firms are capturing

[31]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 (μ is an estimated parameter held constant in the counterfactual). The counterfactuals should therefore be interpreted as estimates for fixing directional distortion conditional on entry.

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 large, to achieve efficiency we need a vaccine-specific entry cost subsidy equal to 30.3 percent of π_B. Panel D shows that an AMC paying the first inventor of any Covid-19 invention a subsidy equal to the social surplus of their invention leads to 5 percent too few firms working on vaccines.[32]

Note why the AMC does not fully resolve directional distortions. Scaling up π_j, for all j, shifts some firms with high cost draws for the vaccine and low cost draws for the therapeutic to the vaccine. However, the racing externality remains: in Section 2, the derivation of directional distortions held even when firms were paid the full social surplus of their invention. Paying the AMC only if a vaccine is invented first helps, but still leaves 3 percent too few firms choosing to work on vaccines. To achieve efficiency with an AMC, the AMC would need to pay 2.85 times the private value of the vaccine and be paid only if a vaccine is invented first. However, achieving efficiency with an AMC is much more expensive than with directed cost subsidies ($\$115.81\pi_B$ versus $\$42.56\pi_B$). 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.

4.3 Other Results and Robustness

Does the racing externality help the model explain the data? To answer this question, we compare our baseline model estimates with those of a different model, where we shut down strategic effects by assuming myopic firms. In that model, firms enter assuming they are the first entrant and that no more firms will enter in the future. The model is equally flexible to our baseline model in all other respects. Online Appendix Figure B.3 presents the estimates of this alternative model. Comparing the estimates of both models, we find that shutting down the racing externality worsens the model fit: the mean squared error of the model with myopic firms is 2.6 times higher than our baseline model. The difference between the baseline and the nonstrategic models is especially salient for early entry. As the number of firms that 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. Therefore, cost differentials 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

[32] 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.

Table 6: Planner's solution versus market equilibrium under alternative policy regimes

	Number of firms working on:	
	Vaccine (A)	Non-vaccine (B)
A. Data and model predictions		
Data	81	266
Market equilibrium (model predictions)	80.812	266.188
B. Setting the social payoff of project j to π_j		
Market equilibrium w/ directed cost subsidy of $0.003 \cdot \pi_B$	81.716	265.284
Planner's solution	81.473	265.527
C. Setting the social payoff of project j to $2.7 \cdot \pi_j$		
Market equilibrium w/ directed cost subsidy of $0.303 \cdot \pi_B$	140.521	206.479
Planner's solution	140.449	206.551
D. Market equilibrium using AMCs of size s		
$s = 2.7 \cdot \pi_j$ for both projects	134.347	212.653
$s = 2.7 \cdot \pi_j$ for the vaccine project only	136.113	210.887
$s = 2.85 \cdot \pi_j$ for the vaccine project only	140.068	206.932

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

will substantially affect the expected value of working on a vaccine. Thus, project-specific cost differentials align the planner and the firm choice when there are many firms, mitigating the directional distortion caused by the racing externality.

Although our main estimates concern vaccines versus non-vaccines, in Online Appendix Table B.2, 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 6.825×10^{-5} and 9.859×10^{-5}, 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. We estimate that successful novel drugs are worth 17.9 times as much as repurposed ones in expectation. In our baseline case, the planner would have increased the number of firms working on novel drugs by 16.6%, shifting 28 firms toward that higher-value research. In the counterfactual where firms earn the full social surplus of their invention as profit, 18 more firms work on a novel compound; 34 percent of the gap between the planner optimum and market equilibrium remains due to strategic racing.

For robustness, we replicate our main analysis assuming that the value of Covid-related inventions does not fall to zero after the first invention is found. In particular, we assume that no further entry occurs after that point, that firms can continue to work on the research line they initially entered, and that one additional invention with value $\delta\pi_j$ can be invented.[33] That is, if $\delta = .5$, we assume that following the invention of a vaccine or a therapeutic, one additional invention still has positive value equal to half its ex-ante value. If a vaccine is invented first, this second invention can either be a second vaccine, or a first therapeutic. Likewise, if a therapeutic is invented first, this second invention can either be a second therapeutic or a first vaccine. Online Appendix Table B.3 shows that permitting multiple inventions gives estimates of the effect of directional distortion that are quantitatively similar to our main results. Note that this setting is identical to one where an infinite number of inventions of either type have value, with the value of each consecutive invention being worth a fraction $\frac{\delta r}{r+n_A\lambda_A+n_B\lambda_B}$ of the prior one.

Lastly, we replicate our main analysis assuming that the rates at which projects A and B are invented are 50 percent faster than what the historical data suggest. This exercise allows us to gauge robustness to the scenario in which firms had beliefs that approval times would be faster than normal. Online Appendix Table B.4 shows that our empirical results are similar to our baseline results in this case, with slightly more strategic racing toward therapeutics.

5 Conclusion

Theoretically, we show that when endogenous market structure is accounted for, shocks to the profitability of innovation in a sector change the direction of research and not only its rate. Higher payoffs cause more firms to pursue R&D. Firms do not fully account for how their invention today affects the surplus generated by partial substitutes invented later. The more fractured the market for research, the more each firm overweights short-run profits earned by racing to enter the market first with a mediocre solution. Therefore, when an innovation area becomes more lucrative or easier to enter, strategic interaction in competitive R&D markets leads to too much work on "quick" projects like repurposed drugs and too little work on projects like vaccines.

Empirically, we quantify the size of this directional distortion using a structural model of Covid-19 pharmaceutical innovation that separates strategic racing from other factors that drive project choice, such as cost heterogeneity. Although the rate of Covid-19 research

[33] We also assume that the firm that made the first invention exits the race.

proceeded at an unprecedented historical pace, it initially involved a smaller share of research on vaccines than previous epidemics. Our empirical estimates suggest that the planner would have pushed many more firms to work on vaccines and novel compounds. The primary reason firms worked on less lucrative projects was that they only captured a fraction of the social surplus of their invention. Differences in the cost of R&D on different projects therefore drove decisions. Nonetheless, even if inventors had earned the full social surplus of their inventions, an additional 7 percent would have worked on vaccines had they believed they would face less competition from other researchers. This implies that "neutral policies" such as advance market commitments are unable to fully restore efficiency. Technologically neutral policy in the face of strategic behavior is not in fact neutral.

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Online Appendix

R&D Competition and the Direction of Innovation

by Kevin Bryan, Jorge Lemus, and Guillermo Marshall

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 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.[34] 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.

[34] See https://milkeninstitute.org/covid-19-tracker.

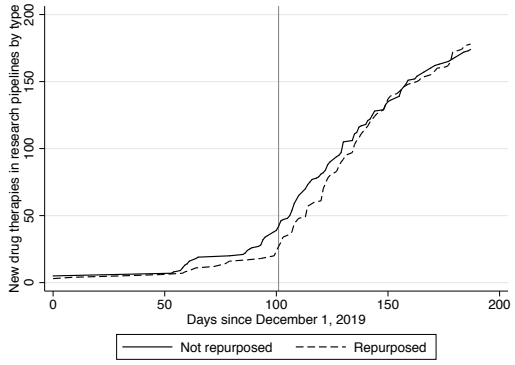
B Additional Tables and Figures

Table B.1: Project choice among Covid-19 entrants (experienced firms subsample)

	Before March 11	After March 11	Total
Non-vaccine	6	27	33
Vaccine	19	28	47
Total	25	55	80

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.

Figure B.1: Number of Covid-19 drug therapies in research pipelines, by drug classification



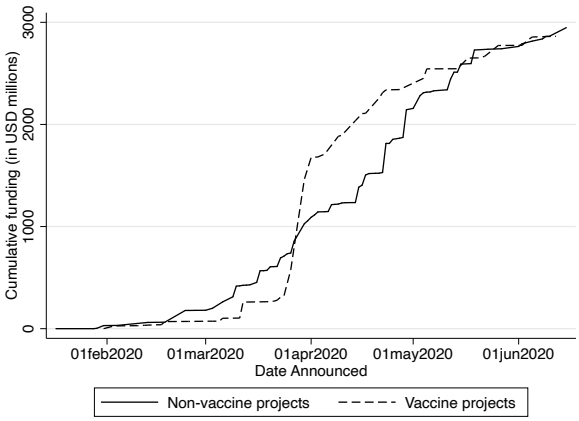
Notes: The figure plots the number of Covid-19 drug therapies (at all stages of development) in research pipelines, by type of drug. The figure separates the drug therapies between repurposed and non-repurposed drugs. Repurposed drugs are defined as drug therapies that existed prior to December 1, 2019 (i.e., beginning of the Covid-19 pandemic) and have more than one indication (e.g., Covid-19 and Ebola).

Table B.2: Planner's solution versus market equilibrium: Repurposed vs. non-repurposed drugs

	Number of firms working on:		Share of firms working on non-repurposed (A):		
	Non-repurposed (A)	Repurposed (B)	Experts	Non-experts	Overall
A. Data and model predictions					
1. Data	169	178	0.788	0.399	0.487
2. Market equilibrium (model predictions)	169.463	177.537	0.788	0.398	0.488
B. Planner's solution					
1. Planner's solution (social payoff$_j = \pi_j$)	171.886	175.114	0.793	0.405	0.495
2. Planner's solution (social payoff$_j = 2.7\pi_j$)	197.520	149.480	0.845	0.485	0.569
C. Counterfactual market equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	187.960	159.040	0.825	0.456	0.542

Notes: The estimates of the parameters of the model are $\hat{\pi}_A = 17.854$, $\sigma_{\text{Non-experienced}} = 1.443$, $\sigma_{\text{Experienced}} = 0.389$, and the parameter estimates of the entry rate of firms and the distribution of firm types are identical to those in Table 4. The values of λ_A, λ_B, and r are set at 0.00006825, 0.00009859, and $1.1^{1/365} - 1$, respectively. As in Table 4, the values of λ_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 4. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the market equilibrium and planner's solution are computed based on the average outcomes across 25,000 simulations of the game.

Figure B.2: Funding by project type



Notes: The figure plots the cumulative public funding pledges over time by type of project (source: Policy Cures).

Table B.3: Planner's solution versus market equilibrium when allowing for two consecutive races

Panel 1: $\delta = 0.1$

	Number of firms working on:		Share of firms working on vaccines (A):		
	Vaccines (A)	Non-vaccines (B)	Experts	Non-experts	Overall
A. Data and model predictions					
1. Data	81	266	0.588	0.127	0.233
2. Market equilibrium (model predictions)	80.816	266.184	0.587	0.127	0.233
B. Planner's solution					
1. Planner's solution (social payoff$_j = \pi_j$)	81.476	265.524	0.592	0.128	0.235
2. Planner's solution (social payoff$_j = 2.7\pi_j$)	139.565	207.435	0.752	0.297	0.402
C. Counterfactual market equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	134.582	212.418	0.744	0.281	0.388

Panel 2: $\delta = 0.5$

	Number of firms working on:		Share of firms working on vaccines (A):		
	Vaccines (A)	Non-vaccines (B)	Experts	Non-experts	Overall
A. Data and model predictions					
1. Data	81	266	0.588	0.127	0.233
2. Market equilibrium (model predictions)	80.815	266.185	0.587	0.127	0.233
B. Planner's solution					
1. Planner's solution (social payoff$_j = \pi_j$)	81.510	265.490	0.592	0.128	0.235
2. Planner's solution (social payoff$_j = 2.7\pi_j$)	135.229	211.771	0.746	0.283	0.390
C. Counterfactual market equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	127.455	219.545	0.710	0.264	0.367

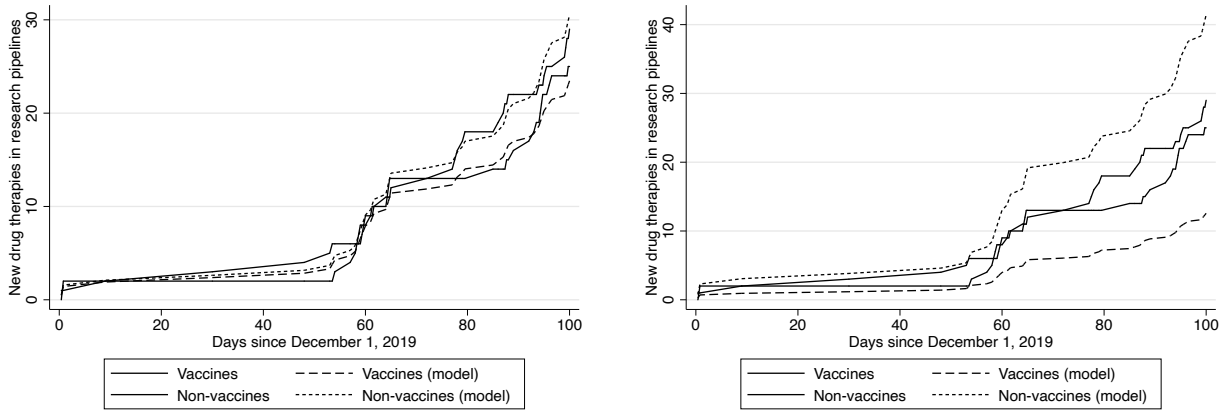
Notes: The estimates of the parameters of the model in Panel A are $\hat{\pi}_A = 37.302$, $\sigma_{\text{Non-experienced}} = 3.651$, and $\sigma_{\text{Experienced}} = 1.008$; the in Panel B are $\hat{\pi}_A = 28.199$, $\sigma_{\text{Non-experienced}} = 3.659$, and $\sigma_{\text{Experienced}} = 1.010$. The parameter estimates of the entry rate of firms, the distribution of firm types, and the calibrated parameters are identical to those in Table 4. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the market equilibrium and planner's solution are computed based on the average outcomes across 25,000 simulations of the game.

Table B.4: Planner's solution versus market equilibrium when λ_j's are 50% faster

	Number of firms working on:		Share of firms working on vaccines (A):		
	Vaccines (A)	Non-vaccines (B)	Experts	Non-experts	Overall
A. Data and model predictions					
1. Data	81	266	0.588	0.127	0.233
2. Market equilibrium (model predictions)	80.814	266.186	0.587	0.127	0.233
B. Planner's solution					
1. Planner's solution (social payoff$_j = \pi_j$)	82.611	264.389	0.596	0.131	0.238
2. Planner's solution (social payoff$_j = 2.7\pi_j$)	138.977	208.023	0.752	0.295	0.401
C. Counterfactual market equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	130.162	216.838	0.734	0.267	0.375

Notes: The estimates of the parameters of the model are $\hat{\pi}_A = 33.316$, $\sigma_{\text{Non-experienced}} = 3.591$, $\sigma_{\text{Experienced}} = 0.989$, and the parameter estimates of the entry rate of firms and the distribution of firm types are identical to those in Table 4. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the market equilibrium and planner's solution are computed based on the average outcomes across 25,000 simulations of the game.

Figure B.3: 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 market 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 Likelihood Function

The probability that there is no discovery in $[0, \tau]$, the next firm enters at time τ, its type is θ, 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

$$\begin{aligned} l_j(\delta) \;=\; & \text{vaccine}_j \cdot \log(F_\theta(V^A_{n_A+1,n_B} - V^B_{n_A,n_B+1})) \\ & +(1 - \text{vaccine}_j) \cdot \log(1 - F_\theta(V^A_{n_A+1,n_B} - V^B_{n_A,n_B+1})) \\ & +\text{After March 11}_j \cdot (\log(\mu_{\text{After March 11}}) - \mu_{\text{After March 11}} \cdot \text{time to next entry}_j) \\ & +(1 - \text{After March 11}_j) \cdot (\log(\mu_{\text{Before March 11}}) - \mu_{\text{Before March 11}} \cdot \text{time to next entry}_j) \\ & +\text{After March 11}_j \cdot (\text{experienced}_j \cdot \log(\kappa_{\text{After March 11}}) \\ & +(1 - \text{experienced}_j) \cdot \log(1 - \kappa_{\text{After March 11}})) \\ & +(1 - \text{After March 11}_j) \cdot (\text{experienced}_j \cdot \log(\kappa_{\text{Before March 11}}) \\ & +(1 - \text{experienced}_j) \cdot \log(1 - \kappa_{\text{Before March 11}})), \end{aligned}$$

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

D Competition and Directional Choice: Anecdotal Evidence from Expert Interviews

To what extent do we observe this racing behavior directly? Firms generally do not make their rationale for choosing one R&D project over another observable to the analyst. However, we do see suggestive evidence of our mechanism at play in qualitative data from a four-month Covid-related entrepreneurship program run in the Spring and Summer of 2020, which for anonymity reasons we call the Program. In the Program, 65 science-based startups from around the world participated in monthly, structured online meetings with a panel of entrepreneurship experts which included serial founders, partners at leading venture capital firms, and world-renowned scientists and epidemiologists. Many of the founders had deep technical expertise but little business experience. At each meeting, the panel gave firms advice on the long-run financial viability of their Covid-related business. We therefore can observe, qualitatively, the interaction between technical potential and financial viability. Although these companies are largely not pharmaceutical companies, the tradeoff of being "first" versus being "best" came up frequently in the online meetings. Consider the following cases.

One firm, headed by senior academics at a top global research university, had developed a technique for a new type of vaccine which is particularly promising when it comes to coronaviruses in particular. In an early summer meeting, the former director of a large government health body evaluated the firm as a "brilliant company. Currently, lots of competitors in vaccine space, but this approach is so far superior." By August, a half dozen different mentors told the company the vaccine space was simply too competitive for them to succeed even if their approach was superior: "This is a very competitive space. Point of differentiation in relation to competitors is very important. There is a race to the forefront in this crowded space." The advice in the final meeting was to either stop working on Covid-19 altogether and focus on a broader scientific problem, or to license out any aspects of the Covid-19 technology which can speed up development for a more advanced competitor.

A second firm, also founded by academics at a top global research university, produced a sensor which could identify pathogens on surfaces or in water. Their technology could detect contaminated surfaces on-site, without the use of specialized equipment or trained clinicians. Although the mentors "like the team" and believe "there is good technical knowledge," even by June there was widespread agreement that "this is becoming a crowded space, so understanding the current players/emerging competition is critical." Even though the firm's technology was quicker and more accurate than existing competitors, its cost and time to

commercial development were too high compared to easier-to-develop technologies such as strong surface cleaners. The company pivoted away from Covid-19 development. Note that in both cases, there was general agreement that the proposed invention was the leader on technical grounds. However, there was so much competition in both markets that modest partial substitutes which arrived to market first were expected to take much of the profit.

E Empirical Stock Price Reaction to Vaccine News

The empirical model in this paper uses revealed preference based on the ex-ante profitability of a novel vaccine or therapeutic. This is necessary since in many cases of directional invention, some projects are never invented along the equilibrium path. We estimate that a Covid vaccine is worth, in expectation, 40 times the mean value of a successful Covid therapeutic. In this appendix, we show the observed share price reaction of the firms who invented the vaccines whose Phase 3 trials ended in 2020.

Figure B.4

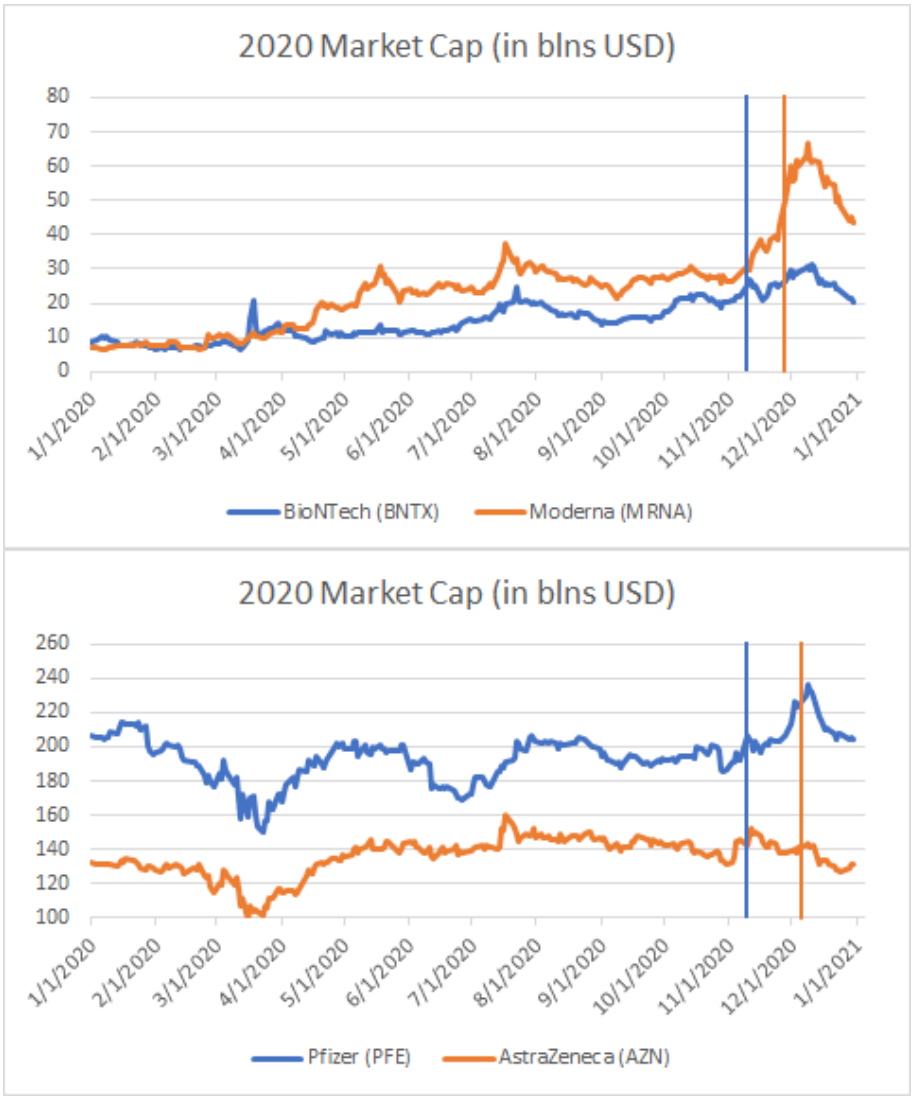


Figure B.4 shows the market cap in USD for Pfizer, BioNTech, Moderna and AstraZeneca throughout 2020. The blue vertical line represent the date of the announcement of a successful

Phase 3 trial for Pfizer and BioNTech (November 9), the orange line in the top panel the successful Phase 3 trial announcement for Moderna (November 30), and the orange line in the bottom panel the date of the successful Phase 3 trial announcement from AstraZeneca (December 8). These announcements are of course not clean event studies due to the reporting of the intermediate trial data, but nonetheless suggest the interrelation between profitability of various manufacturers, and the rough magnitude of the value of a successful vaccine.

On November 9, Pfizer and BioNTech jointly saw their market capitalization rise 18.8 billion USD. On the same day, AstraZeneca fell 3.9 billion and Moderna rose 1.5 billion, partially reflecting the joint positive news of a successful mRNA vaccine and the negative news of a successful rival. On November 30, Moderna announced full results of its Phase 3 trial with efficacy similar to Pfizer/BioNTech. It's market cap went up a further 10.1 billion USD, while AstraZeneca's market cap rose 0.8 billion, BioNTech's rose 3.4 billion, and Pfizer's rose 6.0 billion, again reflecting a combination of positive technological news and negative competition news. Finally, the announcements of AstraZeneca's interim results with only moderate efficacy compared to the mRNA vaccines led to a 1.2 billion dollar market cap improvement for AstraZeneca, but a 4.1 billion dollar jump in Moderna's market cap, a 0.5 billion dollar increase in BioNTech, and a 7.3 billion dollar increase for Pfizer.

It is difficult to interpret the ex-ante value of the vaccine in and of itself to the profitability of large, multiproduct firms like Pfizer and AstraZeneca. Nonetheless, for small firms like Moderna and BioNTech, the year over year increase in market capitalization between January 2020 and the end of that year gives a rough approximation. This value will of course also include the potential profitability of future products built using mRNA technology, or licenses thereof. In 2020, the market cap of Moderna rose 36.6 billion dollars, on a base of just over 7 billion dollars. BioNTech saw a rise of 11.5 billion dollars, from a base of roughly 9 billion. Note, of course, that some of the profitability of BioNTech's product is shared with Pfizer.

F Analysis of the Model

Optimal Direction (Lemma 1). This proposition follows from Bryan and Lemus (2017), Proposition 2, part 1 (p. 259). The note after the proposition comes from noting that when $N \to \infty$, $\frac{N\lambda_B}{r+N\lambda_B} \to 1$, so $P_A \to \pi_{1,A} + \pi_{2,B}$ and $P_B \to \pi_{1,B} + \pi_{2,A}$; and $\frac{N(\lambda_B - \lambda_A)}{r+\lambda_A} \to \frac{\lambda_B - \lambda_A}{\lambda_A}$.

Efficient Entry (Proposition 1).

1. Consider an exogenous payoff shifter η, where η multiplicatively scales all payoffs π. Then, the optimal number of firms is

$$\max_{N \in \{0,1,\ldots\}} V(N)\eta - F \cdot N$$

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

2. As $\eta \to \infty$, we have that $N^*(\eta) \to \infty$. This implies that $\frac{N^*(\eta)\lambda_B}{r+N^*(\eta)\lambda_B} \to 1$. 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 Bryan and Lemus (2017), Corollary 1 (p.260).

Entry and Direction in Equilibrium (Proposition 2)

Part i: Let η scale multiplicatively all payoffs. Let Π^e represent equilibrium profits in a symmetric equilibrium. The equilibrium number of firms N^e with payoff shifter η is determined by the condition

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

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

Part ii: Note that as $N^e \to \infty$ we have $P_A \to \pi_{1,A} + \pi_{2,B}$, $P_B \to \pi_{1,B} + \pi_{2,A}$, $\Delta(N) \to \frac{\lambda_B - \lambda_A}{\lambda_A}$. Therefore, for N^e large enough we will have

$$\lambda_A P_A < \lambda_B P_B - \Delta(N)\lambda_A P_A + N(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A}).$$

Excessive Entry (Proposition 3)

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

$$G(N) = \frac{r\lambda_A}{(r + N\lambda_A)^2}\left(\pi_A + \frac{N\lambda_B}{r + N\lambda_B}V_A\right) + \frac{N\lambda_A}{r + N\lambda_A}\frac{r\lambda_B}{(r + N\lambda_B)^2}V_A.$$

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

Suppose that N 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 N firms will direct their capacity towards the remaining invention. Ignoring the integer constraint, the zero profit condition is $H(N) = F$ where

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

Denote the solution to this equation N^e. Given that $x_{i,j} \leq 1$ and $z_j \leq N$, we have $H(N)N \to \Omega$ as $N \to \infty$, with $\Omega > 0$. This shows that, as $N \to \infty$, there will be a threshold $\bar{N}$ such that $H(N) > G(N)$ for all $N \geq \bar{N}$. As the severity of the crises increases and both N^* and N^e are above $\bar{N}$, we will have $H(N^e) = F = G(N^*) < H(N^*)$. 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 $N^e > N^*$.

G Flow Cost Payoffs

Suppose that instead of receiving a lump-sum payment, the inventors receive a flow payoff until the next invention is discovered.

Let π_i be flow (monopoly) profit when the first invention is i, conditional on nothing else yet discovered. After the first invention there will be full effort to discover the second invention, which will arrive according to the distribution $F(t) = 1 - e^{-\lambda_{-i} N t}$.

Let $\pi^M_{i,-i}$ the payoff to the first inventor after the second invention, when the first invention is i, the second invention is $-i$ and the same inventor discovered both of them.

Let $\pi^D_{i,-i}$ the payoff of the first inventor discovered i and the second invention, $-i$, is discovered by someone else. Note that, because after the first invention, regardless of who invents, there will be full effort in the second invention, the payoff of the second inventor, conditional on not inventing the first invention, denoted π^E, affects entry but does not impact directional choices.

At the beginning of the game incentives are symmetric. Therefore, the inventors expect the following payoff for inventing i first:

$$\int_0^\infty \left\{ \pi_i e^{-N\lambda_{-i} t} + \lambda_{-i} N e^{-N\lambda_{-i} t} \left[\frac{1}{N} \cdot \frac{\pi^M_{i,-i}}{r} + \left(\frac{N-1}{N} \right) \cdot \frac{\pi^D_{i,-i}}{r} \right] \right\} e^{-rt} dt$$

This is the same as

$$V_{f,i} = \frac{\pi_i}{N\lambda_{-i} + r} + \frac{N\lambda_{-i}}{N\lambda_{-i} + r} \left[\frac{1}{N} \cdot \frac{\pi^M_{i,-i}}{r} + \left(\frac{N-1}{N} \right) \frac{\pi^D_{i,-i}}{r} \right] \tag{6}$$

Comparing with our baseline setting, where the first inventor receives an lump-sum payoff $\pi_{1,i}$ and a continuation payoff $\dfrac{N\lambda_{-i}}{N\lambda_{-i} + r} \pi_{2,-i}$, we note two differences:

1. The "immediate payoff" ($\pi_{i,1}$) now is $\dfrac{\pi_i}{N\lambda_{-i} + r}$ which depends on N and λ.
2. The "continuation payoff" ($\pi_{-i,2}$) now is $\frac{1}{N} \cdot \frac{\pi^S_{i,-i}}{r} + \left(\frac{N-1}{N} \right) \frac{\pi^E_{i,-i}}{r}$ and depends on N.

Assuming that starting from A is efficient, instead of $(N-1)(\lambda_B \pi_{1,B} - \lambda_A \pi_{1,A})$, the directional

distortion now is

$$\begin{aligned}\Delta &= (N-1)\left(\frac{\lambda_B\pi_B}{\lambda_A N+r}-\frac{\lambda_A\pi_A}{\lambda_B N+r}\right)\\ &= \frac{(N-1)}{(\lambda_2 N+r)(\lambda_1 N+r)}[N(\lambda_2^2\pi_2-\lambda_1^2\pi_1)+r(\pi_2-\pi_1)]\end{aligned}$$

As a function of N the directional distortion increases, but it is bounded: As $N\to\infty$, the directional distortion converges to

$$\Delta_\infty=\frac{\lambda_2^2\pi_2-\lambda_1^2\pi_1}{\lambda_1\lambda_2}.$$

In the limit as $N\to\infty$, the planner starts from A whenever $\pi^D_{A,B}>\pi^D_{B,A}$. Thus, starting from A is not an equilibrium when N is large whenever $\pi^D_{A,B}<\pi^D_{B,A}+\Delta_\infty$. In particular, if $\lambda_2^2\pi_2$ is larger than $\lambda_1^2\pi_1$, i.e., the incentive to race towards the direction with the largest flow payoff.

Connection with lump-sum payoffs. In the main text, we assumed lump-sum payoffs. This is, in fact, a particular case of flow payoffs under restrictions on the relationship between different flow payoffs. Let $\pi_{1,i}=\frac{\pi_i}{r}$ and let $\pi_{2,i}=\frac{\pi^M_{i,i}-\pi_i}{r}$. Then, Equation 6 can be written as

$$\pi_{1,i}+\frac{\lambda_{-i}}{N\lambda_{-i}+1}\pi_{2,i}+\underbrace{\frac{(N-1)\lambda_{-i}}{N\lambda_{-i}+1}(\pi_{i,-i}-\pi_i)}_{\text{cannibalization}}$$

The expression above is exactly the same payoff that a firm gets in the baseline model except for the last term (cannibalization). Cannibalization represents how much lower the original inventor's own payoff is if someone else invents the second invention, $\pi_{i,-i}-\pi_i$. Cannibalization does not affect social surplus, hence the planner payoff is unchanged by assumptions about its extent. Thus, our baseline model is equivalent to one where there are flow payoffs, but there is no own-cannibalization when the two inventions are discovered first by the same inventor.