R&D Competition and the Direction of Innovation*

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Abstract

When innovation in a given field becomes more lucrative, its *direction* can be distorted even as 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 develop a dynamic structural model quantifying the magnitude of this distortion, even when the value of projects which are not invented in equilibrium are not observed. As a case study, we estimate the direction of pharmaceutical innovation during the Covid-19 pandemic, showing strategic distortion away from vaccines. Policy remedies include advance purchase commitments based on ex-ante value, targeted research subsidies, or antitrust exemptions for joint research ventures.

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

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1 Introduction

What happens when innovation in a particular field becomes more valuable? The first-order effect is that the rate of innovation increases. For instance, a complementary invention may make it easier to develop new ideas, such as machine learning breakthroughs for drug discovery. A demand shock can increase payoffs, as with military R&D during the Cold War. Policy changes like stronger patents, innovation prizes, and research subsidies can make innovation more profitable.

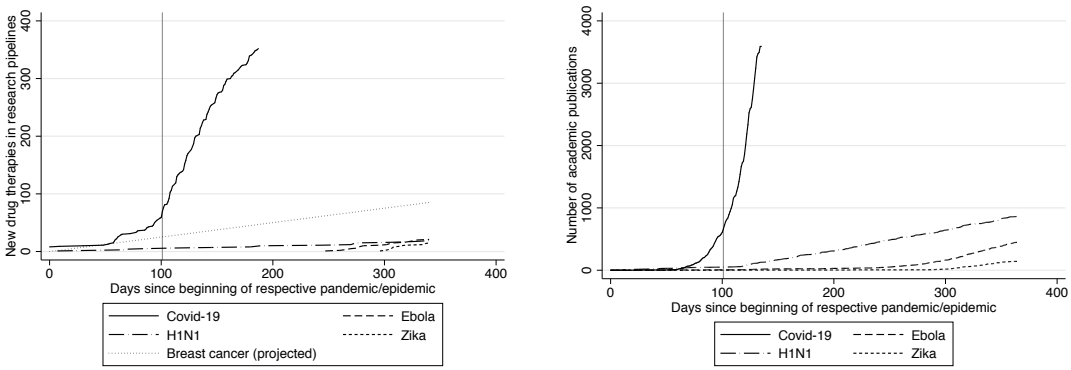
These shifts change more than just the rate of R&D, however. While higher payoffs mean more firms are willing to pay the fixed cost of setting up a research program, this entry changes market structure. Market structure endogenously affects the *direction* of invention. That is, the particular research 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? Firms that work on lower-quality inventions that can be invented quickly will not account for how they decrease the ex-post marginal value of high-quality inventions which are partial substitutes. In equilibrium, the industry becomes more likely to "race" toward projects which can be completed quickly.

We investigate this idea in three ways. First, using a simple model of invention choice with endogenous market structure, we formalize the insight that shifts in payoffs distort the direction of innovation. Second, we show how this distortion can be quantitatively estimated using a structural model. Finally, we estimate the magnitude of this directional distortion using data on pharmaceutical firm project choices in response to the Covid-19 pandemic.

The main empirical challenge is that even when there are many hypothetical inventions in a given innovation race, often only a small number of them are actually invented. The value of hypothetical inventions is therefore not observed, even ex-post. Yet the nature and costs of distorted R&D depend on precisely those hypotheticals. To overcome this challenge, we propose a model of invention choice which we estimate leveraging revealed preference firm R&D, stochastic entry opportunities, and a payoff shock. Potential inventors stochastically arrive and choose which type of invention to work on after observing firm-specific and invention-specific costs. Changes in the distribution of research effort across projects before and after the shock, and dynamically as firms observe how much competition they are facing, identify the payoff to successful inventions and the distributional cost parameters.

To illustrate this model, we exploit the extensive and detailed documentation on pharmaceu-

Figure 1: Panel A shows the number of drug therapies in pharmaceutical pipelines, by pandemic/epidemic. Panel B shows the number of disease-related academic medical publications, by pandemic/epidemic.



A) Therapy Pipelines B) Academic Publications

Notes: The figure plots the number of drug therapies (at all stages of development) in research pipelines, by disease. The beginning of the respective pan/epidemics are December 1, 2019 (Covid-19), April 1, 2015 (Zika), December 1, 2019 (Ebola), and January 1, 2009 (H1N1). Covid-19 therapies measured as of 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. See Section 3.3 for a description of the dataset.

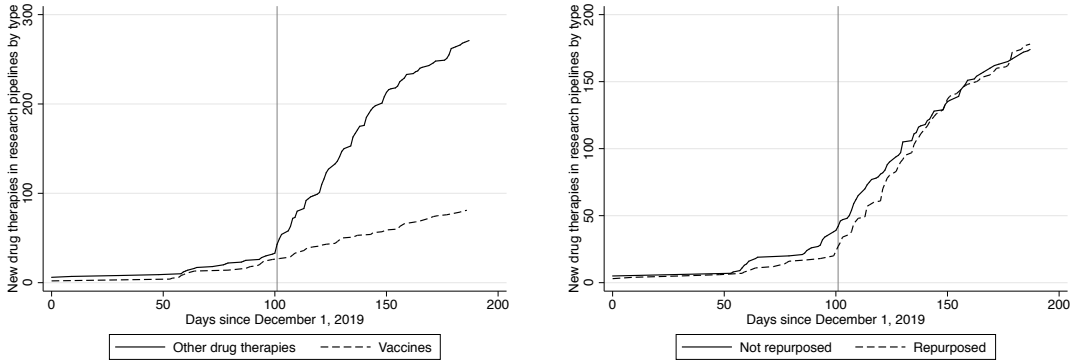
tical development during the Covid-19 pandemic. We use proprietary data on firm characteristics and project choice of entrants during the first six months of the pandemic.[1] This setting is ideal for four reasons. First, there is well-documented data on hundreds of entrants working on Covid-19 projects. 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. Third, there is standardized data on each firm's prior research capabilities. Fourth, we know exactly when the crisis started, and we observe a shock to its severity in early March 2020 when the epidemic globalized.

To help understand the basic theoretical insight, consider the following patterns in Covid-19 related research. Figure 1 shows that the number of both pharmaceutical projects and related academic research articles were an order of magnitude more than any previous epidemic.[2] The incredible rate of invention is often seen as a success story of global drug development. As the pandemic became global in March 2020, the rate of pharmaceutical research rose

[1]Beginning in late May 2020, large vaccine-directed subsidies began to be introduced, such as Operation Warp Speed in the United States. See https://www.hhs.gov/about/news/2020/06/16/fact-sheet-explaining-operation-warp-speed.html.

[2]The 2012 MERS and 2002-2003 SARS epidemics led to only a combined 25 drug therapies in the first year after these outbreaks began. In our analysis, we use December 1st, 2019, as the start date of the Covid-19 outbreak. See, for instance, Wang et al. (2020).

Figure 2: Number of Covid-19 drug therapies in research pipelines, by drug classification



A) Vaccines B) Repurposed

Notes: The figure plots the number of Covid-19 drug therapies (at all stages of development) in research pipelines, by type of drug. Panel A separates the drug therapies between vaccines and all other drug therapies. Panel B 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). See Section 3.3 for a description of the dataset.

yet higher.[3] The *rate* of invention responded strongly both to the importance of the initial epidemic and to the increase in its severity.

The *direction* of invention is more concerning. Compared to H1N1, Ebola, or Zika, Covid-19 research pipelines are skewed towards repurposed drugs and non-vaccine therapies.[4] Following a sharp increase in Covid-19's severity in early March 2020, Figure 2 shows that the rate of entry of vaccines did not change, even as the rate of entry on non-vaccine therapeutics soared. Likewise, the post-March change in the rate of entry of novel compounds to treat Covid-19 fell relative to that of repurposed drugs. Even firms with prior experience developing vaccines became less likely to enter with a Covid-19 vaccine relative to therapeutics.

This is consistent with our theory. Firms developing therapeutics do not care that their successful invention of a decent-but-imperfect drug lowers the ex-post value of a vaccine invented later by someone else. Firms considering the development of vaccines realize that by the time they invent, modest therapeutics are likely to have been invented by someone else: competition is too intense to win the race. Since payoffs depend on the ex-post value

[3]This is perhaps natural given the severity of Covid-19: its death toll has far exceeded recent viral outbreaks including H1N1 (2009), Ebola (2013-2016), or Zika (2015-2016). As of October 1, 2020, there have been one million confirmed deaths worldwide from Covid-19. In contrast, there were 11,323 deaths from Ebola; 18,036 deaths from H1N1, and zero reported deaths from Zika within the first year of the outbreak.

[4]Repurposed drugs are quicker to develop but are less well-targeted (Strittmatter, 2014). Vaccines are more challenging to develop than antiviral therapies (Lurie et al., 2020). Snyder et al. (2020) estimate the expected social value of an optimal vaccine development program is on the order of $3 trillion.

of an invention, the vaccine will therefore be less valuable ex-post than ex-ante.

Anecdotal evidence from top researchers taking part in an elite, international Covid recovery entrepreneurship program who were considering directing effort towards the Covid-19 research support this idea. These researchers were discouraged from entering the Covid-19 race, given the highly competitive landscape, although having top researchers working on a potential solution is arguably socially valuable (for more details, see Online Appendix C). Even among experienced firms, Merck, who brought to market four of the seven new vaccines approved in the U.S. between 1995 and 2019, failed to enter vaccine development with vigor. Press reports suggested that Merck did not want to divert R&D resources from thriving areas to unproven vaccine technology which were believed to be 12-18 months away from success.[5] Evidence from past crises also point towards the importance of the ex-post value of an invention. Indeed, "[a] decade ago, after the H1N1 influenza pandemic fizzled out, the governments of America and various European countries backed out of promised contracts, leaving pharmaceutical companies holding the bag which contained hundreds of millions of dollars of development costs."[6] This "fizzling out" of profits, well-understood to be a potential consequence of a lack of government commitment, is in our model endogenous to the R&D choices made by all firms.

In the absence of directional distortions, our structural model estimates 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, 7.7 percent remains even if we assume pharmaceutical firms earned the full social surplus of their inventions: strategic racing rather than just underappropration slowed vaccine development. Empirically, we estimate fairly substantial firm-specific R&D cost differences for vaccines versus therapeutics. For entrants in Summer 2020, after there has already been substantial entry and the probability of inventing first has become small, project choice is therefore heavily driven primarily by costs rather than strategic behavior. In innovation settings where cost heterogeneity among late entrants is less severe, or the rate of entry of competitors early on is particularly quick, strategic racing can be even more severe.

Our results contribute to three long-running literatures in innovation policy. First, we contribute to the nascent literature on innovation policy and empirical direction. Budish et al. (2015) show that there is too little R&D on diseases whose necessary clinical trials are longer, because the effective term of patent protection after a drug reaches the market is therefore

[5] See https://www.wsj.com/articles/why-merck-is-playing-catch-up-in-the-coronavirus-vaccine-chase-11603470832.

[6] economist.com/briefing/2020/04/16/can-the-world-find-a-good-covid-19-vaccine-quickly-enough

shorter. Moser (2005) suggests, using evidence from 19th century World's Fairs, that inventors in countries without strong patent protection shifted effort toward inventions which can be protected by secrecy, such as Swiss watches. Acemoglu (2002) develops a canonical model of directed technical change showing how factor scarcity and inventor subsidies change what is invented, while Acemoglu et al. (2012) gives an application to optimal climate change policy. Competition in the invention sector is assumed to be monopolistically competitive, with an implicitly fixed market structure. 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 market structure, a first-order concern precisely when changes in the economic environment make inventions related to a given problem more important.

Second, there is the question of how market structure relates to the *rate* of invention. Schumpeter famously argued that while competitive markets have static benefits, quasi-rents are important for covering the fixed costs of innovation.[7] The debate which builds on Schumpeter is particularly complex when market structure is affected by innovation policy. We show there is also an economically-consequential relationship between endogenous market structure and the direction of innovation. Facially-neutral policies targeted at the rate of invention, like patents, may not work as intended during crises since those policies themselves affect market structure.

Finally, our results are related to the largely historical literature about how governments consider the tradeoffs between various innovation policies.[8] Prizes were common even in the 18th century particularly to solve urgent military problems like that of longitude when sailing and the canning of food for Napoleon's troops (Khan, 2015). The U.S. government formed a Patent Compensation Board in 1946 to buy out nuclear energy inventions in the early days of the Cold War (Shavell and Van Ypersele, 2001; Kremer, 1998). Patents arose to protect less-powerful inventors from Venetian politicking (Comino et al., 2020). Just as governments have used these special innovation schemes to avoid favoritism, commitment problems, and excess market power, attention must also be paid to how policy affects invention direction.

[7] See Shapiro (2011) on the "Arrow" and "Schumpeter" perspectives on this question.

[8] On the tradeoff between patents, prizes, and other inducements more generally, see, (e.g. Wright, 1983; Weyl and Tirole, 2012; Galasso, 2020).

2 A Model of Directional Inefficiency

In this section, we present a simple framework to analyze the impact of an unexpected *innovation shifter* in a particular industry such a demand or technology shock that scales up the payoffs of all inventions, or a new regulatory policy that make it less burdensome for firms to enter. This innovation shifter induces entry, which exacerbates R&D competition among inventors and pushes them to "race" toward easier and lower-value inventions, 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 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 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 5 when nothing has been invented yet. Once the vaccine is discovered, the marginal benefit of the drug falls to, say, 3, since less treatment is needed in a partially immunized population. Likewise, if the drug is invented first, the marginal benefit of the vaccine A may fall to 7 since effective therapeutics will lead only high-risk populations to vaccinate. In this case, $\pi_{1,A} = 10$, $\pi_{1,B} = 5$, $\pi_{2,A} = 7$, and $\pi_{2,B} = 3$. For exposition, we present our results with lump-sum payoffs, interpreted as an infinitely long patent on a narrow invention. In Online Appendix F, we relax this assumption and we study the case of flow payoffs that are interrupted by new discoveries.

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.[9] 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

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

inventions have been discovered.

Innovation Shifter: An 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 $\eta \geq 1$, which measures the intensity of the innovation shift.

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.[10] That is, there is no gap between the surplus inventors earn and the social value of their inventions. Second, we assume that project A is difficult, yet valuable (a *long-term project*), whereas B is easier, yet less valuable (a *short-term project*). That is, $\pi_{1,A} + \pi_{2,B} > \pi_{1,B} + \pi_{2,A}$ and $\lambda_B > \lambda_A$.[11] For instance, A may be a vaccine and B a therapeutic during an epidemic, or A a fully renewable power source and B a carbon emissions mitigation tool in the context of global warming. 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.

All proofs are contained in Online Appendix E.

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

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

[10] 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. 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.

[11] 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.

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 $e^{-(\lambda_A x_A + \lambda_B x_B)}$, and the rate at which project k is invented is $\lambda_k x_k$.

Lemma 1. *The planner optimally allocates all researchers to project A first and then to project B if and only if:*[12]

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

As N grows arbitrary large, (2) becomes $\pi_{1,A} + \pi_{2,B} \geq \pi_{1,B} + \pi_{2,A}$, i.e., for sufficiently high N, the optimal project is the more difficult, long-term project A. 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 direction with N firms. The optimal number of active firms, denoted by N^*, is the solution to

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

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

Proposition 1. *We have:*

1. *An innovation shifter makes it socially optimal to increase the number of firms.*

[12] 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.

2. *When the innovation shift is intense (η is 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 Firm 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 will invent it first with a uniform probability.

Let $a_{-ij} = \sum_{k \neq i} x_{kj}$ be the cumulative effort by firms other than i on project j, and let $\tilde{P}_j = \pi_{1,j} + V_j$. 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 innovation shifter weakly increases the number of firms in a symmetric equilibrium.*
2. *When the innovation shift is intense (η is 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 firm 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.[13]

To sum things 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

[13]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.

"first" rather than "best".[14]

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. *An innovation shifter causes over-entry in equilibrium relative to the optimal number of firms.*

When the entry of each firm involves business stealing, entry is more valuable to firms than to society (e.g. Mankiw and Whinston, 1986). 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.

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. In the following section, we extend this model and allow for more flexibility to structurally estimate the extent of the directional inefficiency. Once we have quantitative magnitudes in hand, we will return to solutions for directional distortions in the Discussion.

Before moving to this structural estimation, note two features which we abstract away from in the theoretical model, but which matter enormously for empirical research direction. First,

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

we assume above there is no heterogeneity across firms, either in their type (e.g., those with vaccine-making experience) or within types (e.g., two experienced firms may vary in their precise ability to work on Covid therapies). In practice, many firms work on particular R&D projects not only because of a strategic choice, but because of a difference in capabilities. We will therefore directly estimate, in the empirics, heterogeneity in research costs. Second, heterogeneity across different projects means that the fraction of social surplus earned by inventors matters for project choice since it affects the ratio of payoffs to fixed entry costs. In the theory, we have assumed a single fixed cost paid to enter R&D overall, in order to clarify the nature of the directional distortion and to retain analytic tractability. Again, in the empirics, we will drop this assumption, allowing us to investigate not only the extent of directional racing, but also how it compares to underprovision of valuable projects due to underappropriation of their social surplus.

3 Estimating the Magnitude of Directional Inefficiency

Consider an analyst who has access to the following data in a particular area of innovation. The analyst observes what project is chosen by each firm, the time the firm begins research on that project, and a binary variable denoting whether the firm has prior experience on similar projects of each type. The expected payoff of research of each type is unobserved, as are the fixed costs of entry which may depend on the project the firm works on and its prior experience. Even ex-post, payoffs may be unobservable both because it is their expectation rather than realization which matters for behavior, and because there are projects which may never be invented in equilibrium. We are interested in two questions. First, can we identify the key primitives that drive project choice (i.e., expected payoffs and entry costs)? Second, if so, and if the observed data differs from the model's prediction of the social planner's optimum, what is the impact of competition on this directional inefficiency?

In order to quantitatively match real-world data, we need to 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).

We model project choice conditional on entry. We do not formally model the decision to enter the race. That is, firms enter at an exogenous rate in the model. While this modeling choice is a limitation, there are at least two reasons that lead us to this choice. First, we do not have information on firms that considered entry but decided against. Second, this allows us to remain agnostic about the mechanisms that determine the exact entry time of a given firm. Our empirical focus is on the impact of competition on project choice rather than the broader determinants and timing of entry. Given this assumption about entry, we model an innovation shifter as an increase in the entry rate of firms.

Our primary quantity of interest is the fraction of firms who work on the planner-optimal project conditional on entry. To estimate this quantity, let us first describe the full empirical model, specifying which parameters are calibrated and which are free. We then discuss what variation identifies each of the free parameters.

The innovation shifter that we consider is the global pandemic declaration of Covid-19.[15] After providing descriptive evidence of the nature of entry into Covid-19 research, we describe how we will estimate the model. Finally, we will take this model to Covid-19 data, and discuss the racing behavior we estimate in that setting.

3.1 Empirical model

There is a set of potential entrants. Each entrant has a type $\theta \in \Theta$, and the distribution of types is common knowledge. Firms enter sequentially and the difference between the arrival time of two consecutive firms is $\tau_{\text{entry}} \sim \exp(\mu)$. We assume that the type and entry time of a firm are independent random variables. Upon entry, a firm chooses whether to pursue project A or project B.

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. We assume that no more than $\bar{N}$ firms can enter per project.[16] 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

[15] 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.

[16] 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.

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, firm j wins the race with flow probability λ_j, in which case it receives a payoff of π_j.[17] 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 A, the game will transition to the state $(n_A + 1, n_B)$; if the new firm chooses B, the game will transition to the state $(n_A, n_B + 1)$.

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

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

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

Given that we impose a limit on the total number of firms that can enter each project, and that firms enter at rate μ, there is a time T such that all the firms have entered provided that no project has been invented. We can analytically compute the payoff of a firm working on project j at this time T, and use these payoffs to solve the game by backward induction.[18]

[17] 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.

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

We find the unique equilibrium of the game using this recursive procedure.

3.2 Identification

Assume that firms can be classified in types $\theta \in \Theta$ based on observable covariates. For example, there may be firms with observable experience in a given type of research, and those without. Let there exist one unexpected innovation shifter with a date that is known to the researcher. As discussed in Section 2, an innovation shifter increases the payoff of all inventions relative to the entry costs in a given area and 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.

We therefore have the following set of parameters: 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 $\kappa(\theta)_{t_1}$ and $\kappa(\theta)_{t_2}$.[19]

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. The discount rate is given by the modeler. Let the continuation values $\pi_{2,A}$ and $\pi_{2,B}$ be set to zero in a baseline case, or to a fixed function of π_A and π_B otherwise. For example, assume that the second invention in a given class is worth half the value of the first invention, the third is worth half that, and so on. In this case, the discount rate, the arrival rates λ_j, and the estimated value π_A fully determine $\pi_{2,A}$ and $\pi_{2,B}$.

Without observing the payoff to realized inventions, it is not possible to separately identify λ_j and π_j. Intuitively, firms may enter a given invention contest slowly because its payoff is low when invented, or because it will take a long time to invent and hence the payoff is heavily discounted. Observing the ex-post time until invention is only possible for those that are invented in equilibrium. Even there, we do not want to conflate an invention that was found quickly by good luck with the ex-ante belief by inventors that it would be so easy. We also note that 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. We therefore choose λ_A and λ_B to match historical normal rates of development of an invention of a given type being

[19] 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.

developed by a single firm.

The remaining parameters are free. We leverage revealed preference to identify the payoff of project A, π_A, which in our empirical application is the slow-to-invent 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.

3.3 Descriptive Evidence from Covid-19 Pipelines

Before estimating entry into Covid-19 research structurally, we present descriptive evidence to examine the state of 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. We complement these data with information from public sources, including disease-related academic publications on PubMed and information about recent viral epidemics. See Online Appendix Section A for details about the data construction.[20]

Recall from Figure 1 that the rate of Covid-19 therapies in research pipelines, and the publication rate of Covid-19 articles in academic medical journals, both exceed that of Ebola, Zika, H1N1, and even breast cancer by at least an order of magnitude.[21] Forty-one of these drug therapies were already undergoing clinical trials as of June 15, 2020 (8 are at phase I, 15

[20] 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.

[21] 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).

Table 1: Share of repurposed and vaccine drug therapies, by disease

	Repurposed			Vaccine			Total drug
	Count	Share	p-value	Count	Share	p-value	therapies
Covid-19	178	.506		52	.230		352
Ebola	7	.333	0.127	10	.476	.041	21
Zika	1	.066	0	12	.800	0	15
H1N1	0	.000	0	14	.737	0	19

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

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.

Examining Figure 1 (Panel A), there is a clear visual break in the rate at which therapies entered pharmaceutical pipelines roughly 100 days after the beginning of the outbreak. This coincides with the spread of large-scale community infection outside of Asia, the first large-scale regional lockdown outside of China (in Northern Italy, on March 8, 2020), and the global stock market decline (the Dow Jones lost nearly 1/3 of its value between March 4 and March 23, 2020). In the analysis that follows, we will delineate this increase in the severity of Covid-19 with the March 11, 2020 WHO declaration of a global pandemic.[22]

Though the rate of Covid-19 entry is very high, especially after mid-March, the type of entry shows striking patterns. Table 1 shows that Covid-19 therapies are less likely to be vaccines, and more likely to be repurposed, than therapies developed for Ebola, Zika, or H1N1.[23] Figure 2 in the Introduction shows entry by type over time.[24] The relative trend toward repurposed therapies and away from vaccines grows even stronger after the perceived severity of the pandemic increases in early March. 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.[25]

[22]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.

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

[24]Online Appendix Table A.2 decomposes all Covid-19 drug therapies by drug classification.

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

Table 2: Pipeline composition of firms by involvement in other viral outbreaks

	A) Covid-19			B) H1N1			C) Ebola			D) Zika		
	Other	Entrants	Diff.	Other	Entrants	Diff.	Other	Entrants	Diff.	Other	Entrants	Diff.
Vaccine	.287	.268	-.019	.341	.438	.098	.332	.229	-.103	.317	.786	.469
			[.455]			[.028]			[.046]			[0]
Antiviral	.441	.438	-.004	.503	.738	.235	.495	.8	.305	.486	.929	.443
			[.899]			[0]			[0]			[0]
Infectious	.536	.534	-.003	.586	.777	.191	.571	.857	.286	.585	.929	.343
			[.92]			[0]			[0]			[0]
Any of above	.544	.597	.053	.59	.806	.215	.578	.863	.285	.593	.933	.34
			[.047]			[0]			[0]			[0]
Number of firms	3,549	297		1,508	58		2,234	27		2,624	22	

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

Can firm experience explain these patterns? Table 2 (Panel A) shows the comparison between the pre-existing pipeline of firms currently involved in the development of a Covid-19 drug therapy versus all other pharmaceutical firms in our dataset. Firms addressing the Covid-19 pandemic are about equally likely to have developed vaccines, antivirals, and drug therapies for infectious diseases as those not involved in Covid-19. That is, experience with similar diseases does not seem to predict entry into the race for a Covid-19 drug therapy. This was not true in previous smaller epidemics, where firms that developed a drug therapy were far more experienced both overall and in developing vaccines, antivirals, and drug therapies for infectious diseases. In addition, a comparison across panels shows that firms working on therapies for Ebola, Zika, or H1N1 were much more likely to have had experience in related diseases than the firms working on Covid-19.[26]

Just as Covid-19 entrants overall are less experienced than entrants in previous smaller epidemics, Table 3 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.[27] Firms that enter after March 11th are 17.7 percentage

therapies are being led by a firm in East Asia.

[26]Online Appendix Table A.3 shows that this distinction holds in a probit regression of entry on experience with similar diseases even when we condition on firm size and age. For example, the table shows that prior experience developing vaccines is generally less predictive of entry into Covid-19 than entry into the other diseases.

[27]We note that the direction and statistical significance of the differences in firm observables in Table 3

Table 3: 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.

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.

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. We estimate this regression using the full sample of Covid-19 entrants and also using the subsample of firms that have had a vaccine project and a drug project for an infectious disease prior to Covid-19 in their research pipelines (henceforth, *experienced firms*). It is reasonable to assume that these experienced firms have the know-how to develop a Covid-19 vaccine, or at least they are better equipped than firms without prior experience to handle this task.

Table 4 shows a negative and statistically significant coefficient on the post March 11 dummy, which indicates that firms that enter after March 11th are less likely to work on vaccines (all else equal). This is true for all firms (Table 4, Column 1), but also true for the subset of

are robust to dropping the five largest firms developing a Covid-19 drug therapy, which have developed more than 400 drug therapies each in the past and are currently developing a combined total of 16 drug therapies (either as the lead firm or a partner). The same holds true for the other results presented in this section.

experienced firms (Table 4, Column 2).[28] 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.[29]

Table 4: Project choice among Covid-19 entrants: Logit regressions

	(1)	(2)
		Experienced
	All firms	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.

Let us sum up the descriptive evidence. The direction of Covid-19 drug development involves a much greater percentage of non-vaccine therapies and repurposed drugs than prior epidemics. This directional tilt became even stronger after the pandemic increased in severity in early March 2020. Covid-19 attracted entry from a much less specialized set of firms

[28] Online Appendix Table A.4 shows that 76 percent of experienced firms that entered before March 11 chose to develop a vaccine, while only 51 percent of experienced firms that entered after March 11 did so.

[29] Online Appendix Figure A.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."

than prior epidemics, and again the post-March 11 entrants are yet less experienced and specialized. Intuitively, this may be seen as resulting from the higher payoffs to Covid-19 inventions attracting entry even from firms that are not experienced in antivirals, vaccines, or infectious diseases. Finally, the post-March 11 decline in vaccine and novel compound drug development is not solely the result of increased entry by less experienced firms: there is a trend away from these projects even conditional on firm experience and prior drug portfolios.

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.

3.4 Structural Estimation

In the estimation, we assume that there are two types of firms: experienced and non-experienced, so $\Theta = \{\text{Experienced, Non-experienced}\}$. We define experienced firms as those who have had a vaccine project and a drug project for an infectious disease in their research pipelines prior to Covid-19. We set the values of the rates at which the different types of projects are invented to $\lambda_A = 0.0000555$, $\lambda_B = 0.00007607$, which are estimates based on historical data on approval times of drugs for infectious diseases, and reflect that vaccines have historically taken longer to develop (Lurie et al., 2020).[30] We set the daily discount rate to $r = 1.1^{(1/365)} - 1$, which is a common assumption in the literature. Lastly, as noted, we make a scale normalization and set the payoff of the non-vaccine drug to 1 ($\pi_B = 1$). In this way, our estimates of the payoff of a vaccine (π_A) and the costs of developing each type of project are measured relative to the payoff of a non-vaccine drug. Note that π_j are expected payoffs, so even though we impose within-class homogeneity in this expectation, the model allows different vaccines and therapeutics to vary in their ex-post value.

To capture the structural break in the entry rate of new firms, we assume that there is an exogenous (and unanticipated) change in the rate of arrival of new firms after March 11. Implicitly, this can be thought of as resulting from an unexpected shock to payoffs of all Covid-19 related inventions. Similarly, we allow for an exogenous change in the composition

[30]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.

of potential entrants to reflect that fewer experienced firms entered after March 11.[31] 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 $\sigma(\theta) > 0$ 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.[32]

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 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 compo-

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

[32] 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, i.e., cost differences cannot be greater than π_B in absolute value.

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

4 Results

Table 5 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.[33]

To gauge model fit, Figure 3 plots the raw data versus the predictions of the model for the number of vaccine and non-vaccine projects over time. The figure shows the average number of vaccine and non-vaccines over 25,000 simulations of the model using the estimated parameters. As the figure shows, the model matches closely the number of firms in each project at every moment in time. The first two rows of Table 6 also show that the model accurately predicts the share of firms of each type that are working on vaccines and drug therapies.

Using the model estimates, we perform two exercises. First, we measure the extent of directional efficiency by solving for the socially efficient allocation of firms across projects. We assume that the social planner controls whether to allocate 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

[33] 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 D, 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.

Table 5: 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: $\lambda_A = .0000555$, $\lambda_B = .00007607$, and $r = 1.1^{1/365} - 1$ (time is expressed in days in the model).

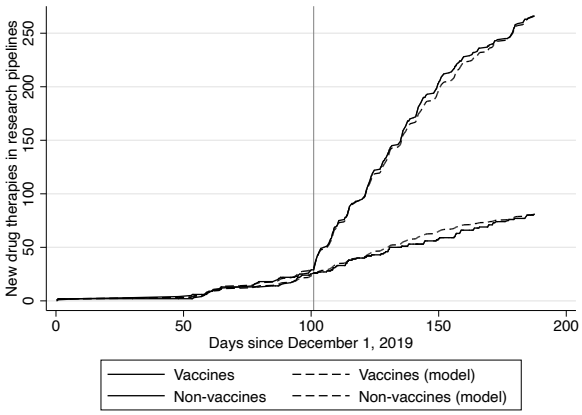
(1998) that, if willingness to pay for medical treatments is proportional to income, the social surplus is 2.7x the fixed-price revenue of a monopolist inventor.[34] As before, we run 25,000 simulations of the social planner's problem and compute the outcomes for each simulation.

Second, we recompute the firm equilibrium 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 6 compares simulation-average planner optima to the expected outcomes in the firm

[34]This estimate comes from assuming that willingness to pay for medical treatment is proportional to income. Using U.S. income distribution data, the gap between the total surplus of a medical invention and the profit earned by a fixed-price monopolist is 2.7.

Figure 3: Number of vaccine and non-vaccine drug therapies predicted by the model and in the data



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

equilibrium. In the baseline case, in line with observed data (A.1), the model equilibrium involves 80.8 firms working on a vaccine project (A.2). However, 140.5 firms would be assigned 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 firm 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 6 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.[35] 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 6 C.2 and C.3 show the importance of beliefs about competition. C.2 considers the counterfactual where all firms believed that the entry rate of R&D competition would have

[35]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 6: Planner's solution versus firm equilibrium

	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. Firm 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 Firm 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 firm equilibrium and planner's solution are computed averaging outcomes across 25,000 simulations of the game. 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.

always been as high as it was post-March 11, when we estimate a firm enters Covid R&D every .3 days. In this scenario, we retain the assumption that firms earn the full social surplus of their invention. Nonetheless, only 107.9 firms begin 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. C.3 shows that, to the contrary, had firms always believed competition would remain limited to its pre-March 11 level, many more of these late entrants would have worked on vaccines: indeed, there would have been over-entry, especially from less experienced firms.

4.1 Other Results and Robustness

The model does not bake in a necessary racing externality to explain the data. In Online Appendix Figure A.3, we show the results of solving the model shutting down strategic effects; that is, firms enter assuming they are the first entrant, and that no firms will enter in the future, but otherwise the model is equally flexible. The mean squared error of this model is 2.6 times higher than our full model. The difference between the full model and a nonstrategic model is especially salient when it comes to early entry. As the number of firms who have entered grows large, and no invention has yet arrived, the expected payoff for any

invention becomes small due to the high level of competition. Cost differentials therefore begin to drive project choice, and hence nonstrategic models will fit well. However, when few firms have entered, an expectation that the next few firms will work on a quick therapeutic will have a substantial effect on the expected value of working on a vaccine.

Although our main estimates concern vaccines versus non-vaccines, in Online Appendix Table A.5, we replicate our analysis redefining the two possible projects to be a novel drug (project A) and a repurposed drug (project B). As in Section 2, a repurposed drug is defined as one that has more than one indication and which existed prior to the Covid-19 pandemic. A novel drug is one that is not repurposed. Based on historical data on drug approval times, we set the values of λ_A and λ_B to 0.00006825 and 0.00009859, respectively. The value of r and the definition of experienced firms are the same as those used for the vaccine/non-vaccine drug analysis with which we lead this section. 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 firm equilibirum remains due to strategic racing.

For robustness, we replicate our main analysis assuming that the value of Covid-related inventions do 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.[36] 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 A.6 shows that permitting a further invention causes only a small change in our estimates of the directional distortion. Note that this setting is identical to a setting where an infinite number of inventions of either type have value, with the value of each consecutive invention being worth a fraction $\delta\frac{r}{r+n_A\lambda_A+n_B\lambda_B}$ 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

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

faster than normal. Online Appendix Table A.7 shows that our empirical results are similar to our baseline results in this case, with slightly more strategic racing toward therapeutics.

5 Discussion and Implications

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 begin research on a particular problem. The more fractured the market for research, the less any one firm weighs the total value of the market against the profits earned by racing to enter the market first with a mediocre solution. Therefore, 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.

We further show how the size of this directional distortion can be structurally estimated. The structural model permits a separation of strategic racing from other factors that drive project choice, such as heterogeneities in the ability of some firms to pursue certain projects. This economic insight and structural model can be applied, in principle, to many competitive innovation settings. We show an empirical case using the wealth of documentation that exists for the Covid-19 pandemic. Although the rate of Covid-19 research proceeded at an unprecedented historical pace, it initially involved more research on short-term solutions than previous epidemics. This trend was exacerbated when Covid-19 became a global pandemic in March 2020. Our 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, an additional 7 percent of firms would have worked on vaccines had they believed they would face less competition from other researchers.

The distortion we identify is *ex-ante*: it shifts what firms invent rather than the deadweight loss they generate ex-post if, for example, they have a patent. Prior research suggests that vaccines may be underprovided due to the difficulty of extracting this ex-post surplus. For instance, Kremer and Snyder (2015) argue that for rare but serious diseases, when consumer valuation for treatment is highly heterogeneous, it is easier to extract this surplus with treatments than vaccines. We have assumed away this possibility by giving inventors the entire social surplus, yet vaccines are still underprovided. Vaccines may also be underprovided due to a commitment problem on the part of the government. Kremer et al. (2020) argue

for advance purchase commitments partly on these grounds: pharmaceutical firms otherwise believe their vaccines will be expropriated after the cost of research has been incurred.[37]

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

Our model, both theoretical and structural, applies to problems beyond Covid-19. Consider a wartime government hoping to incentivize new aircraft, or an IGO that wants to see effective novel climate change mitigation technology. Assume that they credibly commit to pay the full, ex-post social value of any completed invention within their bailiwick. Doing so may be *worse* than paying lower rewards if the induced competition pushes firms to work on second-best technology that can be completed quickly. This is especially true when the planner prefers firms to work on a difficult, long-run project, where a simpler partial substitute exists, where the R&D market is fragmented, and where these different research projects have similar development costs with limited heterogeneity across firms. Our structural model permits retrospective analyses of these distortions even when the value of different inventions is unknown to the analyst, since we draw on the revealed preference of inventors to infer the magnitude of any distortions.

What can be done? Patent buyouts (Kremer, 1998), where the government buys a patent in order to remove the deadweight loss of monopoly pricing, do not solve our problem. Indeed, by increasing the return to invention, it induces more entry and makes directional distortion worse. The same is true of generic 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 policies will limit this problem. First, the government can allow research joint ventures without antitrust restrictions. Note from the theoretical model that the total surplus for the industry is decreasing in the extent of deviation. In April 2020, Sanofi and GlaxoSmithKline,

[37] 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.

normally rivals, formed a joint research venture to develop a Covid-19 vaccine.[38] Research joint ventures on projects that are expected to be harder to invent than most inventions in a sector ought to be encouraged.[39]

Second, targeted subsidies, incentivizing only difficult, high-value inventions, while permitting unsubsidized research on other projects, simultaneously induce entry while avoiding a directional distortion. Targeted subsidies generally have a bad name: many innovation scholars do not like the government to "pick winners". However, in some cases the nature of high-value inventions is often widely known. There is no ambiguity, for instance, about the therapeutic properties of the highest-value remedies for Covid-19. Indeed, 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.[40]

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 committing to pay the *ex-ante* social value of an invention, even if future inventions lower their value, can completely remedy directional inefficiency. Estimates of the value of targeted Covid-19 vaccine AMCs argue that an advance commitment of nearly $40 billion, with coordinated allocation to high risk populations, increases welfare by avoiding ex-post bidding wars for potentially limited vaccine supplies (Snyder et al., 2020). Our results suggest that optimal vaccine AMCs, or alternatively vaccine cost subsidies, need to be higher yet given the strategic distortions induced by high overall Covid-19 payoffs.

[38] 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.

[39] See Grossman and Shapiro (1986) for a deeper analysis of the antitrust issues with research collaborations.

[40] A group of prominent economists argued in the May 4th, 2020 issue of the New York Times discussed existing large subsidy programs for Covid-19 inventions, but noted that they were targeted broadly at "diagnostics, therapeutics, and treatments" rather than vaccines (Athey et al., 2020).

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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.[41] 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.

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

B Additional Tables and Figures

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

Country	Freq.	Percent	Cum.
Australia	4	1.14	1.14
Austria	4	1.14	2.28
Belgium	4	1.14	3.42
Canada	19	5.41	8.83
China	10	2.85	11.68
Denmark	1	0.28	11.97
France	10	2.85	14.81
Germany	7	1.99	16.81
India	2	0.57	17.38
Ireland	3	0.85	18.23
Israel	8	2.28	20.51
Italy	4	1.14	21.65
Japan	10	2.85	24.50
Korea (South)	10	2.85	27.35
Netherlands	4	1.14	28.49
Norway	1	0.28	28.77
Russia	2	0.57	29.34
Scotland	1	0.28	29.63
Spain	5	1.42	31.05
Sweden	5	1.42	32.48
Switzerland	12	3.42	35.90
Taiwan	1	0.28	36.18
Turkey	1	0.28	36.47
United Kingdom	12	3.42	39.89
United States	211	60.11	100.00

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

Table A.2: Covid-19 drug therapies, by drug classification

Type	Not repurposed	Repurposed	Total
Biologic	60	62	122
Device	0	1	1
New Molecular Entity (NME)	19	99	118
Non-NME	12	13	25
Unknown	2	0	2
Vaccine	78	3	81
Total	171	178	349

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

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

	Covid-19	Ebola	H1N1	Zika
Experience w/ vaccines	0.314***	0.346*	0.824***	1.255***
	(0.120)	(0.208)	(0.212)	(0.223)
Experience w/ antivirals	0.555***	0.500*	0.630**	4.419***
	(0.134)	(0.260)	(0.268)	(0.163)
Experience w/ infectious diseases	0.108	0.632**	0.087	-3.595***
	(0.125)	(0.298)	(0.243)	(0.251)
Controls:		Firm age, firm size		
Observations	3475	2237	1516	2625
R^2				

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

Table A.4: Project choice among Covid-19 entrants (experienced firms subsample)

	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.

Table A.5: Planner's solution versus firm 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. Firm 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 firm 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 5. 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 5, 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 5. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the firm equilibrium and planner's solution are computed based on the average outcomes across 25,000 simulations of the game.

Table A.6: Planner's solution versus firm 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. Firm 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 firm 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. Firm 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 firm equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	127.455	219.545	0.710	0.264	0.367

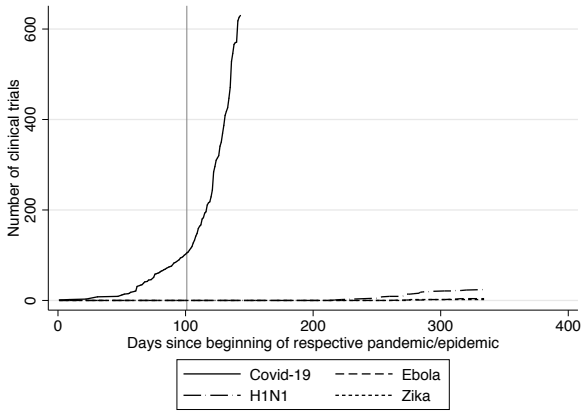
Notes: The estimates of the parameters of the model in Panel A are $\hat{\pi}_A = 37.302$, $\sigma_{\text{Non-experienced}} = 3.651$, and $\sigma_{\text{Experienced}} = 1.008$; the in Panel B are $\hat{\pi}_A = 28.199$, $\sigma_{\text{Non-experienced}} = 3.659$, and $\sigma_{\text{Experienced}} = 1.010$. The parameter estimates of the entry rate of firms, the distribution of firm types, and the calibrated parameters are identical to those in Table 5. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the firm equilibrium and planner's solution are computed based on the average outcomes across 25,000 simulations of the game.

Table A.7: Planner's solution versus firm 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. Firm 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 firm equilibria					
Private payoff$_j = 2.7\pi_j$. Entry belief:					
1. Match the data	130.162	216.838	0.734	0.267	0.375

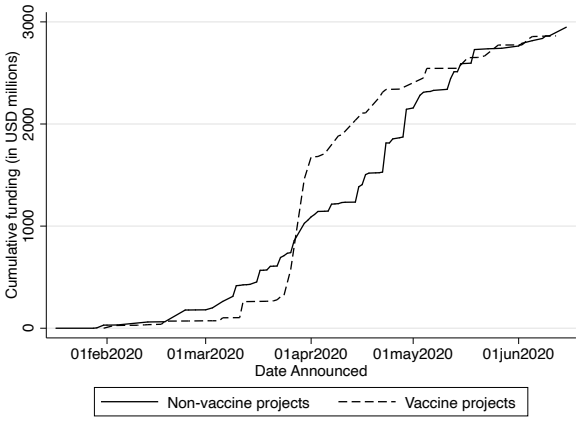
Notes: The estimates of the parameters of the model are $\hat{\pi}_A = 33.316$, $\sigma_{\text{Non-experienced}} = 3.591$, $\sigma_{\text{Experienced}} = 0.989$, and the parameter estimates of the entry rate of firms and the distribution of firm types are identical to those in Table 5. Outcomes are measured at 188 days since December 1, 2019. Outcomes for the firm equilibrium and planner's solution are computed based on the average outcomes across 25,000 simulations of the game.

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



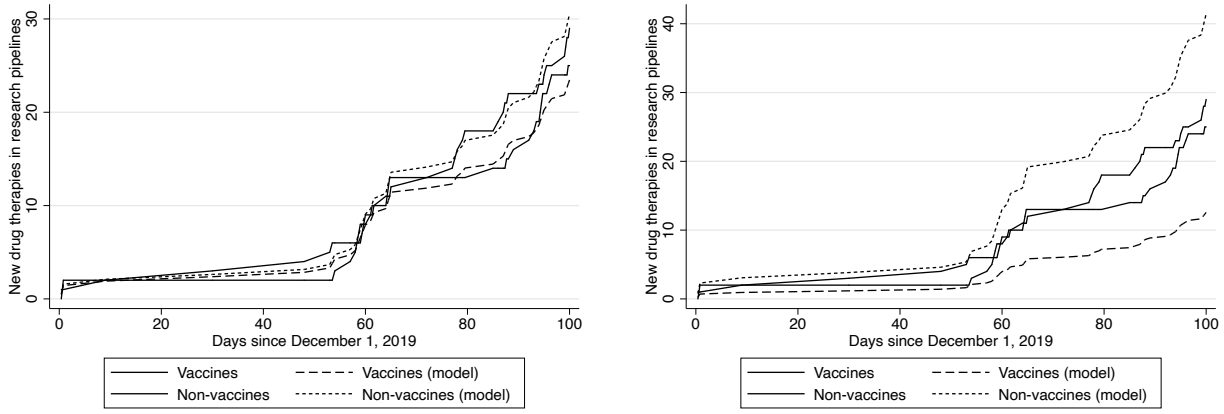
Notes: The figure plots the number of clinical trials (all stages) during the first year after the start of the viral outbreak, by disease. We use data from clinicaltrials.gov. We note that a given drug therapy may undergo multiple clinical trials. The beginning of the respective pan/epidemics are December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

Figure A.2: Funding by project type



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

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

C 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.

D 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 A.4

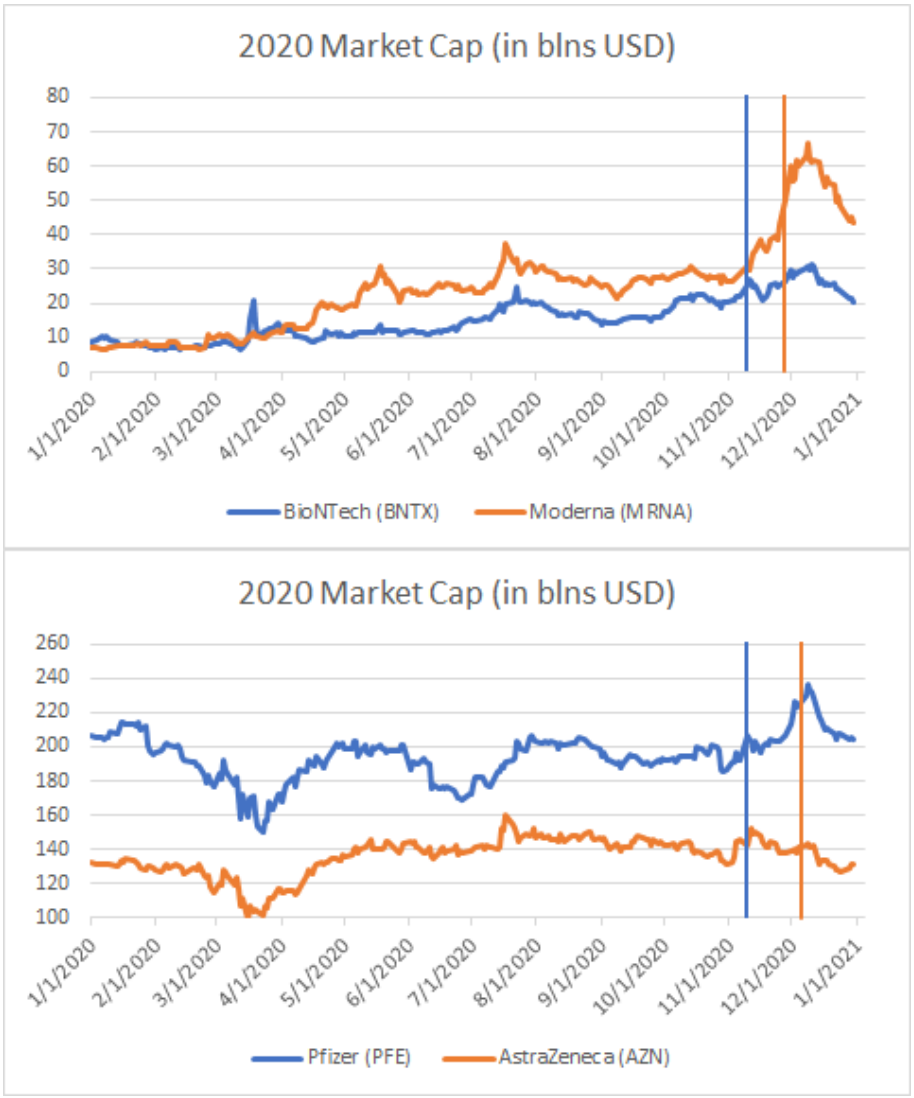


Figure A.4 shows the market cap in USD for Pfizer, BioNTech, Moderna and AstraZeneca throughout 2020. The blue vertical line represent the date of the announcement of a successful

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.

E 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 innovation 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 innovation 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 innovation 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 $N^e > N^*$.

F 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.