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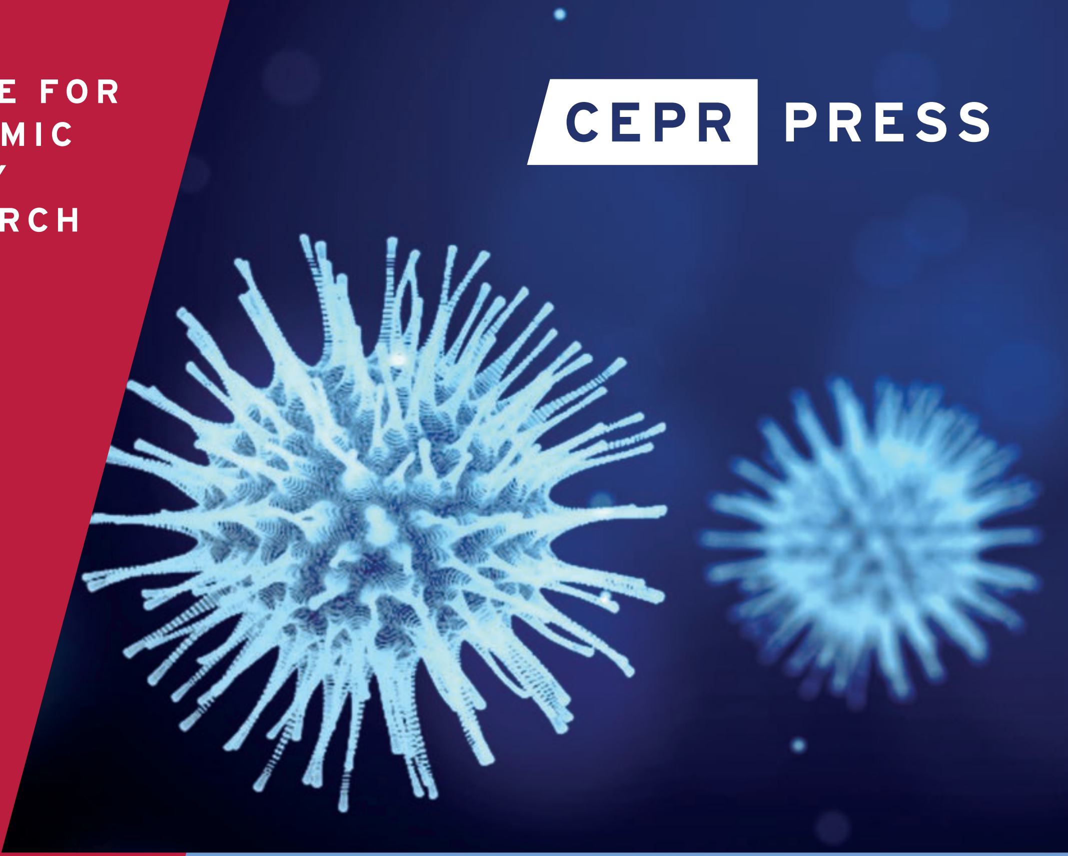

# COVID ECONOMICS

## VETTED AND REAL-TIME PAPERS

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# Covid Economics
# Vetted and Real-Time Papers

*Covid Economics, Vetted and Real-Time Papers*, from CEPR, brings together formal investigations on the economic issues emanating from the Covid outbreak, based on explicit theory and/or empirical evidence, to improve the knowledge base.

**Founder**: Beatrice Weder di Mauro, President of CEPR
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*Covid Economics* will feature high quality analyses of economic aspects of the health crisis. However, the pandemic also raises a number of complex ethical issues. Economists tend to think about trade-offs, in this case lives vs. costs, patient selection at a time of scarcity, and more. In the spirit of academic freedom, neither the Editors of *Covid Economics* nor CEPR take a stand on these issues and therefore do not bear any responsibility for views expressed in the articles.

# Submission to professional journals

The following journals have indicated that they will accept submissions of papers featured in *Covid Economics* because they are working papers. Most expect revised versions. This list will be updated regularly.

*American Economic Review*
*American Economic Review, Applied Economics*
*American Economic Review, Insights*
*American Economic Review, Economic Policy*
*American Economic Review, Macroeconomics*
*American Economic Review, Microeconomics*
*American Journal of Health Economics*
*Canadian Journal of Economics*
*Econometrica**
*Economic Journal*
*Economics of Disasters and Climate Change*
*International Economic Review*
*Journal of Development Economics*
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*Journal of Monetary Economics*
*Journal of Public Economics*
*Journal of Public Finance and Public Choice*
*Journal of Political Economy*
*Journal of Population Economics*
*Quarterly Journal of Economics*
*Review of Corporate Finance Studies**
*Review of Economics and Statistics*
*Review of Economic Studies**
*Review of Financial Studies*

(*) Must be a significantly revised and extended version of the paper featured in *Covid Economics*.

# Covid Economics
# Vetted and Real-Time Papers

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*Covid Economics* **Issue 55, 4 November 2020**

# Optimal testing and social distancing of individuals with private health signals

Thomas Tröger[1]

Date submitted: 29 October 2020; Date accepted: 29 October 2020

*We consider individuals who are privately informed about the probability of being infected by a potentially dangerous disease. Depending on its private health signal, an individual may assign a positive or negative value to getting tested for the disease. Individuals dislike social distancing. The government has scarce testing capacities and scarce resources for enforcing social-distance keeping. We solve the government's problem of setting up an optimal testing-and-social-distancing schedule, taking into account that individuals may lie about their private health signal. Rather than modelling the infection dynamics, we take a snapshot view, that is, we ask what should be done at a particular point in time to curb the current spread of the disease while taking the current well-being of the individuals into account as well. If testing capacities are sufficiently scarce, then it can be optimal to test only a randomly selected fraction of those who want to be tested, and require maximal social distancing precisely for those individuals who wanted a test and ended up not belonging to the tested fraction.*

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## 1 Introduction

[1] Consider an individual who believes that she may have been infected by a virus that is potentially dangerous. Initial symptoms caused by the virus infection can be specific to the particular virus, but also may be rather unspecific. For example, a person who may have been infected by Covid 19 may experience some rather unspecific respiratory problems, but may also experience some more specific symptoms like a loss of her sense of smell. Another typical situation is that the individual has no symptoms at all, but knows that she has been in contact with a possibly infected person. Such an individual faces a dilemma. If she quickly undergoes a test for the disease, then she can expect an early treatment after a positive test result which can be quite beneficial to her health. On the other hand, if she decides to not undergo the test at this point in time, then she avoids the hassle of traveling to and spending time at a test facility, and she avoids the immediate personal quarantine that will result in case her test result is positive.

The government cannot simply advise all individuals with sufficiently severe symptoms or with contacts to possibly infected persons to undergo tests or to remain socially distant, because any individual is, to a large extent, *privately informed* about its health status, that is, an individual can downplay or exaggerate its symptoms when communicating with medical personal, and the individual can conceal or falsely claim recent contacts with possibly infected persons.

In this paper, we analyze how a government should optimally design a testing-and-social-distancing schedule in such a situation. We assume that the government is concerned about both the current well-being of its citizens and curbing the spread of the disease. Any individual that is infected and is not quarantined causes a negative externality on the population of individuals because it may infect others. On the other hand, given that test capacities may be scarce, spending a test unit on any particular individual has an opportunity cost, and in addition there may be a surveillance cost of making sure that the individual keeps any required social distancing or her quarantine.

In contrast to a large fraction of the literature, we do not model the dynamics of the infectious disease, but take a snapshot view. That is, fixing a particular point in time with a particular state of diffusion of the disease, we ask what should a government do in order to curb the current spread of the disease while taking the current well-being of its citizens into account as well. In this sense, our analysis is partial. Nevertheless, it provides very clear insights. These insights should be useful as a building block for a dynamic model that takes the incentive effects into account that we describe.

The most basic insight is that individuals who believe it to be sufficiently unlikely that they are affected, in expectation, lose out from being tested because the small chance of having the disease and thus getting a beneficial early treatment

[1] Funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224, project B1, is gratefully acknowledged.

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is outweighed by the hassle of undergoing a test. On the other hand, individuals who feel sufficiently ill, in expectation, gain from being tested because the expected benefit from an early treatment outweighs the hassle cost of undergoing the test. Formally, there exists a number $p^*$ such that any individual who assigns a probability larger than $p^*$ to the event of being infected expects to gains from undergoing the test, while any individual who believes that she has the disease with a probability smaller than $p^*$ believes that she loses out from undergoing the test.

We call the individual's personal probability assessment of being infected her *type*. We assume that each individual is privately informed about her type.[2] Thus, when communicating with medical personal, she can claim to be of a smaller type than her true type (i.e., downplay her symptoms or conceal her contacts with possibly infected persons) and, alternatively, claim to be of a larger type (i.e., exaggerate her symptoms or claim to have been in contact with a possibly infected person). The population consists of individuals whose types are drawn independently from a given interval of probabilities. The lowest feasible type (which may be equal to 0 or strictly larger than 0) feels quite healthy, while the highest feasible type (which may be equal to 1 or strictly below 1) feels rather ill.

The government sets up a testing-and-social-distancing schedule. That is, it specifies, for each type of individual, a probability of being tested and a degree of social distancing, a real number between 0 and 1, where 1 should be interpreted as quarantine. We take a mechanism-design approach, that is, we allow the government to optimize over all schedules that are mathematically feasible. The optimal schedule turns out to be simple and intuitive.

If individuals could not misrepresent their types, computing the optimal schedule would be straightforward. According to this so-called *first-best solution*, there would exist a threshold type such that all types above the threshold type are tested and all types below the threshold type are not tested; the level of the threshold type depends on the parameters of the environment such as the government's cost of a test, its cost of enforcing any social-distancing requirements, and the weight it puts on an individual's current utility relative to the weight put on curbing the current spread of the disease. Depending on the parameters, it can also be optimal to require maximal social distancing (i.e., quarantine) for a range of types below the threshold type of the testing schedule. That is, it can be optimal to quarantine some individuals rightaway, without testing them first.

A simple, but very important, observation is that, with the exception of some special cases, the first-best solution is not implementable because individuals of certain types have an incentive to downplay or exaggerate their types. For con-

[2] We are not assuming that individuals consciously do calculations with probabilities. Nevertheless, thinking in terms of degrees of likelihood is common sense and is relevant to many aspects of life beginning with the weather forecast. While psychological research has identified many biases in decision-making under uncertainty (e.g., Gigerenzer (2008), Kahneman (2011)), it is fair to say that the individuals in our model face quite simple decision problems, given the optimal testing-and-social-distancing schedules that we propose.

creteness, suppose that the parameters are such that the threshold type of the testing schedule is below $p^*$. Then there exists a range of types that are above the threshold type (and thus are supposed to get tested) and are below $p^*$ (and thus lose out from being tested). Any individual with such a type has an incentive to misrepresent her type by claiming a type below the threshold type so that she avoids being tested. Similarly, if the threshold type of the testing schedule is above $p^*$, individuals of certain types have an incentive to claim a higher type than their true type. Further incentive problems occur if some, but not all, of the untested individuals are to be put in quarantine. These incentive problems prevent the first-best solution from being implementable.

The main contribution of the paper is to solve the government's problem of setting up an optimal testing and social-distancing schedule, while taking the individuals' incentive constraints into account. That is, extending methods from mechanism-design theory, we compute an optimal schedule, taking it as given that any individual is free to lie about her type. The resulting solution is called the second-best optimal schedule.

The second-best optimal schedule generally looks rather different from the first-best schedule—the fact that each individual is privately informed about their health status has a tremendous impact on the nature of the optimal schedule.

We distinguish four different cases concerning the possible nature of the second-best solution. First of all, it can be optimal for the government to test nobody (at the considered point in time) and quarantine everybody; testing nobody should be interpreted here as saving any available testing capacity for a different population of individuals or for use at a different point in time. This extreme solution is incentive compatible because no individual is even asked about their type—the same regulation is enforced on everyone. An example of a situation in which this is the solution is when the government's overwhelming concern is curbing the current spread of the disease, while it can enforce any social-distancing requirements at negligible cost. Let us turn to the other three cases.

Secondly, it can be optimal for the government to not regulate anything. We call this the null mechanism. Here, the government lets any individual decide freely whether or not they want to be tested. No social distancing is required for those who decide not to get tested. As a result, all individuals with types above $p^*$ will be tested, and all individuals with types below $p^*$ will not be tested. We summarize this case by saying that the marginally tested type, denoted $\check{p}$, is equal to $p^*$.

Third, it can be optimal to set up a testing-and-social-distancing schedule such that the marginally tested type, $\check{p}$, is smaller than $p^*$. In other words, there is now an interval of types, from $\check{p}$ to $p^*$, who are supposed to get tested although they lose out from being tested. The trick to make individuals with these types reveal themselves so they can be tested, is to require some social distancing for any individual who decides to remain untested. This lowers the payoff from not getting tested so that, if the level of social distancing is chosen right, individuals of type $\check{p}$ become indifferent between being tested and not being tested. Incen-

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tive compatibility is then satisfied. This form of the testing-and-social-distancing schedule explains why it can be optimal to require some social distancing even for those individuals who are quite sure to not be infected.

The remaining, fourth, possibility for the optimum is that the marginally tested type $\check{p}$ is higher than $p^*$. Now there is an interval of types, from $p^*$ to $\check{p}$, who are supposed to not get tested although they gain from being tested. A solution like this can be optimal if test capacities are rather scarce, that is, if the opportunity cost of a test is very high. How are individuals with types in between $p^*$ and $\check{p}$ prevented from snatching a test by claiming a higher type than their true type? The optimal solution is to introduce probabilistic testing. Only a randomly selected fraction of the individuals who claim to have types above $\check{p}$ are tested. For any individual who claims a type above $\check{p}$, if the randomization implies that this individual does not belong to the tested fraction, maximal social distancing is required. Each individual now faces a gamble if she claims a type above $\check{p}$: on the one hand, this allows her to grab a test with some probability, but, on the other hand, it sends her in quarantine for sure if (through the randomization) she ends up not getting tested. Higher types are more willing than lower types to take such a gamble because for them the test is more valuable, while the hassle of being put in quarantine for those who do not get a test is type-independent.[3]

All four solution cases have in common that at most a binary information is required from each individual: the individual is never asked anything beyond the information whether it feels relatively healthy (type below $\check{p}$) or rather ill (type above $\check{p}$).

In the paper, we also provide some detailed results and examples concerning which of the four solution cases is second-best optimal, depending on the exogeneous parameters of the model, and what are the properties of the optimal testing threshold $\check{p}$.

## Literature

There is a huge epidemiological literature that analyzes the dynamics of infectious diseases.[4] A small subset of this literature investigates behavioral aspects, that is, models individual choices of possibly infected individuals (see the survey by Klein, Laxminarayan, Smith, and Gilligan (2007)). The behavioral aspect that is modelled most frequently is that each individual may choose their level of contacts with other, possibly infected, individuals. A reason for government intervention may arise because of the negative externalities of any contact (see, e.g., Kremer (1996), considering the HIV/AIDS epidemic, and Fenichel, Castillo-Chavez, Ceddia, Chowell, Parra, Hickling, Holloway, Horan, Morin, Perrings, et al. (2011)). By modeling the individual choice of undergoing a test, rather than the choice of

[3]As for a concrete application example, imagine this schedule to be used for the group of individuals who arrive at an airport on a given day if tests are too scarce to test everybody.

[4]See von Thadden (2020) for an adaptation to the epidemiological specifics of the current Covid-19 pandemic.

the level of contacts, we differ sharply from this literature.

An important building block of our model is the assumption that individuals are heterogenous with respect to the individual probability assessments of being infected. Such heterogenous assessments have been modeled by Gong (2015) and, similarly, Paula, Shapira, and Todd (2014), who show empirically for the HIV/AIDS epidemic that these probability assessments are behaviorally relevant. They find that the individual belief has a strong impact on the individual level of contacts. Heterogenous individual health-status beliefs are also modelled in Brotherhood, Kircher, Santos, and Tertilt (2020), who introduce a state of “fever”.

Chen (2006) considers a disease for which, in contrast to the disease we consider, a vaccination is available; each individual chooses whether to get vaccinated, which incurs a personal cost. Due to the incentive effects of a vaccination, its overall welfare effect can be ambiguous.

Caplin and Eliaz (2003), in a static model, combine individual choices of being tested and contact choices that are conditional on a certificate of the test result. Fear of a positive test result is introduced as a psychological bias, and the optimal certification policy of the government is determined.

Testing and social distancing as a design problem of the government has been considered in the literature. Berger, Herkenhoff, and Mongey (2020) recognize the importance of testing asymptomatic individuals and applying conditional quarantine. However, in their model the individuals cannot choose anything, but the government’s policy is applied mechanically to all individuals depending on their health states. Acemoglu, Makhdoumi, Malekian, and Ozdaglar (2020) distinguish agents with high and low values of social contacts who choose their level of contacts in a network. Different types of agents can react differently to policies, and optimal policies are generally type dependent.

Brotherhood, Kircher, Santos, and Tertilt (2020) assume that individuals choose their hours of work, domestic leisure, and leisure outside the house; this choice implies, in particular, a level of contacts with possibly infected persons.[5] The main assumption of the paper is that individuals are heterogeneous with respect to a payoff-relevant observable characteristic, age. The government can, and should, condition its testing and social-distancing policies on this characteristic.[6]

Another strand of the literature models the government’s optimal testing and social distancing policy as a control problem across the evolution of the disease (Piguillem and Shi (2020), Kruse and Strack (2020)).

On a technical level, finding the second-best solution in our model is a mechanism-

[5]Similarly, Jones, Philippon, and Venkateswaran (2020) introduce a choice of shopping time and working time, inducing a level of social contacts.

[6]One way to capture age in our model would be by recognizing that the benefit from early treatment is larger for old people than for young people, giving rise to a smaller threshold probability $p^*$ for old people, and a different second-best optimal schedule in an old population compared to a young population. In order to capture a mixed-age poulation in our model, we would need to define a welfare objective that puts positive weights on the welfare of different age groups and recognizes the possibility of cross-infections.

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design problem in which an individual's required degree of social distancing acts as a quasi-money that steers every individual's incentives to reveal her type. From the individual's point of view, getting tested is like receiving a good that may have a positive or negative value for the individual. The technical challenge of solving the government's problem mainly arises from the fact that the probability of becoming quarantined is restricted between 0 and 1, thus restricting the amount of quasi-money that can be paid by any individual.[7]

## 2 Model

We consider an individual who is uncertain about whether or not she is infected by a given disease. At time 0, the individual possesses a private signal, her type $p \in [\underline{p}, \overline{p}]$, that describes the individual's personal probability assessment that she is infected, given her current symptoms and recent contacts with other people, where $0 \leq \underline{p} \leq \overline{p} \leq 1$. In most applications, it is reasonable to assume that no individual can be absolutely sure to have the disease (i.e., $\overline{p} < 1$), and also never be sure to be healthy (i.e., $\underline{p} > 0$), but our model also encompasses environments in which absolutely certain individuals may exist (i.e., $\underline{p} = 0$ and/or $\overline{p} = 1$). Although our model considers a single individual, it is instructive to imagine a population of individuals out of which the considered individual is a representative member.[8]

We assume that, across the population, individuals' probability assessements are not systematically wrong, that is, for all $p$, among all individuals who think that they are infected with probability $p$, the expected fraction $p$ is in fact infected.[9] Let $F$ denote the c.d.f. for the distribution of types $p$ in the population of individuals. We assume that $F$ has a density $f$ that is strictly positive on the open interval $(\underline{p}, \overline{p})$.

At a point in time after time 0, the individual may develop clearer symptoms, at which point the individual may regret not having learned about its infection at time 0, which would have opened the opportunity to begin an early treatment. Our analysis focusses on time 0.

[7] Again on a technical level, our setup may be seen as a case of mechanism design with costly state-verification (see Ben-Porath, Dekel, and Lipman (2014)). In this literature, a designer commits to verifying states and implementing outcomes conditional on agents' reports when agents have private information related to these states. In our setting, the government is able to verify an individual's health state by testing for the infection, but she is not able to verify the agent's type. The verification of the health state carries a cost not only to the government, but is also costly to the individual.

[8] What defines a population depends on the application. A population may be large, such as the group of citizens in a jurisdiction, or more confined, such as the group of individuals who arrive at an airport on a given day.

[9] A model variation in which agents are systematically too pessimistic or optimistic, or have s-shaped probability distortions as in prospect theory (see Kahneman (2011) for an introduction), may also be considered. A psychological bias towards overestimating the probability of being infected may be considered a plausible model variation in a population with a small rate of infections when the illness nevertheless draws a lot of public attention.

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At time 0, the individual may be tested for the illness. The test perfectly reveals the health state. Getting tested is a hassle for the individual; let $c^t > 0$ denote the individual cost of having the test done. On the other hand, if the test comes out positive, then an early treatment can be started; let $b > 0$ denote the individual's anticipated benefit of being treated early.[10]

Social distancing (starting at time 0) may be enforced on the individual. The degree of social distancing is a real number between 0 and 1. We use the term quarantine to indicate the maximal social-distancing level, 1. For the purposes of the model, any social-distancing level may be thought of as a probability of being put into quarantine.

Being in quarantine is unpleasant; the cost for the individual is denoted $c^q > 0$. We assume that being quarantined is more unpleasant than being tested:

$$c^q \quad > \quad c^t. \tag{1}$$

A quarantined individual cannot spread the disease. Putting an infected individual into quarantine yields a social benefit of $b^q > 0$. Putting a non-infected individual into quarantine has no benefit.

We assume that every positively tested individual will be quarantined, and no negatively tested individual will be quarantined. Thus, an individual of any type $p$ expects to get quarantined with probability $p$ after a test, implying that the individual's *expected value of being tested* is given by

$$v(p) \quad = \quad p(b - c^q) - c^t. \tag{2}$$

We assume that the benefit of the early treatment is so high that the expected value of getting tested is positive for the highest type, that is,

$$\overline{p}(b - c^q) \quad > \quad c^t.$$

The less likely an individual deems itself infected, the smaller the expected value of getting tested; an individual who is sure to be healthy will have a negative value because $v(0) = -c^t < 0$. We assume that the lowest type is so close to 0 that its expected value is negative,

$$\underline{p}(b - c^q) \quad < \quad c^t.$$

The inequalities above mean that there is enough heterogeneity in the population so that a conflict exists between those who, in the absence of any other incentives, would like to get tested and those who do not want to get tested. Let

$$p^* \quad = \quad c^t/(b - c^q) \tag{3}$$

[10] An interesting model extension would distinguish individuals with low $b$ (young, no preexisting illnesses) and high $b$ (old, preexisting illnesses). The social welfare function would then depend on a convex combination of both groups' expected utilities, with the weights depending on the groups' relative sizes in the population. The interaction between the groups would arise from the possibility of cross-group infections.

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denote the indifferent type, that is, $v(p^*) = 0$. By the assumptions above, $\underline{p} < p^* < \overline{p}$.

The government's goal is to set up a rule for determining who gets tested and what level of social distancing will be required.

Even before introducing the government's welfare function, it is pretty clear that the optimal testing-and-social-distancing rule will, in general, be type-dependent. For all $p$, let $m(p)$ denote the probability that an individual of type $p$ is tested, and let $q(p)$ denote the required degree of social distancing for such an individual, conditional on the event that the individual does not get tested. Naturally,

$$0 \leq m(p) \leq 1 \quad \text{for all } p. \tag{4}$$

Similarly, recalling that any degree of social distancing is interpreted as a probability of getting quarantined,

$$0 \leq q(p) \leq 1 \quad \text{for all } p. \tag{5}$$

The pair of functions $(m, q)$ defines the government's rule or (direct) mechanism.

The main difficulty for the government is that, given any individual's personal cost of getting tested and cost of getting quarantined, individuals may lie about their personal health signal. Due to the revelation principle, there is no loss of generality in restricting attention to mechanisms $(m, q)$ that are *incentive compatible*, that is, direct mechanisms in which no individual can gain from making a false claim about her type. In order to spell out this condition, let

$$U(\hat{p}, p) \quad = \quad v(p)m(\hat{p}) - c^q(1 - m(\hat{p}))q(\hat{p}) \tag{6}$$

denote the current expected utility of an individual of any type $p$ who pretends to be of some type $\hat{p}$. The incentive-compability condition requires that

$$U(p, p) \geq U(\hat{p}, p) \quad \text{for all } \ \hat{p} \text{ and } p. \tag{7}$$

Our model does not attempt to capture the dynamic aspects of the spread of the disease. Rather, we are interested in the problem which mechanism is optimal at the given current point in time. Thus, we take it is given that the goverment is concerned about two things: first, the current expected utility of an (average) individual, which should be kept high; second, the probability that any given individual spreads the disease, which should be kept low.

An individual can spread the disease if and only if it is infected and is not quarantined. Let $b^q > 0$ denote the social benefit of quarantining an infected individual. The *expected quarantining benefit* that is achieved by the goverment's rule with respect to type $p$ is equal to

$$b^q(m(p)p + (1 - m(p))pq(p)).$$

This is because, in case the individual is tested (probability $m(p)$), the benefit $b^q$ occurs if and only if the individual is infected (probability $p$) because the test is perfect; if, however, the individual is not tested (probability $1-m(p)$), then being infected (probability $p$) and gettting quarantined (probability $q(p)$) are stochastically independent events, so that the benefit $b^q$ only occurs with probability $pq(p)$.

Denoting the government's welfare weight on the individual's utility by $w^1 > 0$,[11] the government's welfare objective is given by

$$\begin{aligned} W &= E_{p\sim F}\left[w^1 U(p,p) + b^q p\,(m(p) + (1-m(p))q(p))\right. \\ &\qquad \left. - c^{gt} m(p) - c^{gq}(1-m(p))q(p)\right], \end{aligned} \tag{8}$$

where $c^{gt} > 0$ denotes the government's production cost of a test, and $c^{gq} \geq 0$ denotes the government's surveillance cost of enforcing the quarantine of an untested person.[12]

Interpreting $c^{gt}$ as an opportunity cost, we can view $c^{gt}$ as a measure of the current scarcity of test medication units or test facilities, that is, the higher $c^{gt}$ the higher is the cost of using a test unit for any particular individual. In this view, $c^{gt}$ is the government's value of saving a test unit for a different point in time or of using it for an individual outside the considered population of individuals.

The cost $c^{gq}$ can be interpreted as a measure of the availability of surveillance and enforcement infrastructure. Furthermore, $c^{gq}$ can be seen as measuring the lack of social norms towards voluntary quarantine keeping in the considered population of individuals.

Since we do not set up a dynamic model, we cannot determine the optimal value of $w^1$.[13] Instead we identify structural properties of the goverment's current welfare-maximizing rule, taking $w^1$ as a given parameter.

The government's goal is to solve the following (second-best) welfare-maximization problem:

$$\max_{m(\cdot),q(\cdot)} W \quad \text{s.t. } (4), \quad (5), \quad (7),$$

where the expected utilities that occur in (7) are computed via (6).

[11] From a theoretical point of view, $w^1$ is a redundant parameter. The relative weight of the individual utility in the welfare objective could also be captured by scaling the parameters $b$, $c^q$, and $c^t$ appropriately. We keep the parameter $w^1$ for convenience.

[12] For simplicity, we assume that there is no cost of enforcing the quarantine of a positively tested person. While such a cost could be easily incorporated into our model, it is reasonable to assume that a positively tested person will keep its quarantine voluntarily, or the medical facility into which the person is transferred will enforce the quarantine without incurring significant extra costs beyond the cost of caring for and treating the individual.

[13] In a dynamic model, because the fraction of infected individuals in the population becomes a variable, the definition of an agent's current expected utility must be altered such that she obtains a benefit from being healthy. The testing-and-social-distancing rule would be adapted dynamically. The welfare-maximizing value of $w^1$ would depend on the impact of the current spread of the disease on the discounted expected utility of forward-looking agents.

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**First best**

As a benchmark,[14] we now discuss the rule the government would use if it could directly observe the individual's type and thus could set up any rule without relying on the individuals' type reports. Such an omniscient and omnipotent government would solve the following first-best problem:

$$\max_{m(\cdot),q(\cdot)} W \quad \text{s.t.} \;\; (4), \;\; (5).$$

To solve this problem, we replace the expression (6) for $U(p,p)$ in $W$ and rearrange terms,

$$\begin{aligned} W &= E_{p\sim F}\big[w^1\left(v(p)m(p) - c^q(1-m(p))q(p)\right) + b^q p\left(m(p) + (1-m(p))q(p)\right) \\ &\qquad - c^{gt}m(p) - c^{gq}(1-m(p))q(p)\big] \\ &= E_{p\sim F}\left[C(p)m(p) + D(p)(1-m(p))q(p)\right], \end{aligned} \tag{9}$$

where we use the shortcuts

$$C(p) = w^1 v(p) + b^q p - c^{gt}, \tag{10}$$

$$D(p) = -w^1 c^q + b^q p - c^{gq}. \tag{11}$$

Note that both $C$ and $D$ are linear and strictly increasing functions of $p$, and $C$ is steeper than $D$ because $w^1 > 0$.

Using (9), the welfare-maximizing value of $m(p)$ and $q(p)$ can be determined separately for each $p$. Denoting by

$$\underline{p}^q = \frac{w^1 c^q + c^{gq}}{b^q}$$

the number such that $D(\underline{p}^q) = 0$, constraint (5) together with (9) shows that an optimal quarantining schedule is given by[15]

$$q^{**}(p) = \begin{cases} 1 & \text{if } p \geq \underline{p}^q, \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

Using this schedule, the welfare can be expressed as a function of the testing schedule $m$:

$$W = E_{p\sim F}\left[C(p)m(p) + \max\{0, D(p)\}(1-m(p))\right].$$

Thus, by constraint (4), an optimal testing schedule is given by

$$m^{**}(p) = \begin{cases} 1 & \text{if } C(p) - \max\{0, D(p)\} \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

[14] This section can be skipped on first reading.

[15] It is possible that $\underline{p}^q < \underline{p}$, in which case everybody should be quarantined, or $\underline{p}^q \geq \overline{p}$, in which case nobody should be quarantined.

In order to achieve a more explicit form for the optimal testing schedule, we distinguish two cases. Define $\underline{p}^t$ such that $C(\underline{p}^t) = 0$, that is,

$$\underline{p}^t = \frac{w^1 c^t + c^{gt}}{w^1(b - c^q) + b^q}.$$

Suppose first that $C(\underline{p}^q) \geq 0$, that is,

$$\underline{p}^t \leq \underline{p}^q. \tag{13}$$

In this case, $D(p) \leq 0$ for all $p \leq \underline{p}^t$, implying $m^{**}(p) = 0$. For all $p \in (\underline{p}^t, \underline{p}^q]$, we have $C(p) > 0$ and $D(p) \leq 0$, implying $m^{**}(p) = 1$. For all $p > \underline{p}^q$, it is also true that $m^{**}(p) = 1$ because

$$C(p) - D(p) > C(\underline{p}^q) - D(\underline{p}^q) = C(\underline{p}^q) \geq 0,$$

where the first inequality follows from the fact that $C$ is steeper than $D$.

Summarizing the insights so far, we have seen that, if condition (13) holds, then

$$m^{**}(p) = \begin{cases} 1 & \text{if } p \geq \underline{p}^t, \\ 0 & \text{otherwise.} \end{cases}$$

Note that, under condition (13), the optimal quarantining required by (12) never comes to play: due to (13), all types that are optimally quarantined if they are not tested are tested anyway.

Secondly, consider the case in which (13) does not hold, that is, $\underline{p}^q < \underline{p}^t$.

In this case, $C(p) < 0$ for all $p \leq \underline{p}^q$, implying $m^{**}(p) = 0$. For all $p > \underline{p}^q$, we have $D(p) > 0$, implying

$$C(p) - \max\{0, D(p)\} = C(p) - D(p).$$

Let $\underline{p}^{qt}$ be such that $C(\underline{p}^{qt}) - D(\underline{p}^{qt}) = 0$, that is,

$$\underline{p}^{qt} = \frac{c^{gt} - c^{gq} - w^1(c^q - c^t)}{w^1(b - c^q)}.$$

Because $C(\underline{p}^q) - D(\underline{p}^q) = C(\underline{p}^q) < 0$ and $C$ is steeper than $D$, we have

$$\underline{p}^{qt} > \underline{p}^q,$$

and thus

$$m^{**}(p) = \begin{cases} 1 & \text{if } p \geq \underline{p}^{qt}, \\ 0 & \text{otherwise.} \end{cases}$$

Thus, in the case where (13) does not hold, the range of types that are tested is smaller than the range of types that are quarantined. In other words, there is a range of intermediate types that are quarantined rightaway, without a test being applied; only high types are tested. We summarize.

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**Proposition 1.** *A first-best best testing-and-quarantining schedule is given as follows. If condition (13) holds, then an individual is tested if and only if her type is at least* $\underline{p}^t$*; no social distancing is required for untested individuals. If condition (13) fails, then an individual is tested if and only if her type is at least* $\underline{p}^{qt}$*; there is a nonempty interval of types—the types in* $[\underline{p}^q, \underline{p}^{qt})$*—such that an individual with such a type is quarantined rightaway, without being tested; no social distancing is required for individuals with types in* $[\underline{p}, \underline{p}^q)$*.*

We illustrate the first-best via a discussion of the comparative statics with respect to the cost of testing, $c^{gt}$.

If test capacities are abundant (i.e., $c^{gt} \approx 0$), then (13) is satisfied because

$$\underline{p}^t \approx \frac{w^1 c^t}{w^1(b - c^q) + b^q} < \frac{w^1 c^q}{w^1(b - c^q) + b^q} < \frac{w^1 c^q + c^{gq}}{b^q} = \underline{p}^q.$$

All individuals with types above this threshold are tested, and no social distancing is required for untested types. Note that $\underline{p}^t < \underline{p}$ if $\underline{p} > 0$ and $b^q$ is sufficiently large. That is, unless some individuals are almost certainly healthy (i.e., $\underline{p} = 0$), all individuals will be tested if the public benefit $b^q$ is sufficiently large.

As $c^{gt}$ increases, the marginally tested type $\underline{p}^t$ increases, so that fewer and fewer individuals are tested. There exists $c^{gt}$ such that $\underline{p}^t = \underline{p}^q$. If test capacities become even scarcer, (13) fails. The set of tested types shrinks ever more as $c^{gt}$ increases further, but the quarantining threshold $\underline{p}^q$ remains constant.

At some point, test capacity is so scarce that $\underline{p}^{qt} \geq \overline{p}$. Then nobody is tested anymore, but quarantining of individuals with types in the interval $(\underline{p}^q, \overline{p}]$ persists; depending on the parameters, it can be optimal to quarantine nobody (if $\underline{p}^q > \overline{p}$) or everybody (if $\underline{p}^q \leq \underline{p}$).

Figure 1 provides an illustration. It shows an example of the marginally tested type and the marginally quarantined type as functions of the testing cost $c^{gt}$, keeping the other parameters fixed.

A simple, but very important, observation is that, with the exception of extreme cases or non-generic cases, the first-best solution is not incentive compatible. For concreteness, suppose that condition (13) is safisfied and that the parameters are such that individuals with high types should be tested, whereas individuals with sufficiently low types should not be not tested, that is,

$$\underline{p} < \underline{p}^t < \overline{p}.$$

According to (6), in the first-best solution, the payoff of an individual with type $p$ who announces a type $\hat{p}$ is given by

$$U(\hat{p}, p) \quad = \quad \begin{cases} v(p) & \text{if } \hat{p} > \underline{p}^t, \\ 0 & \text{if } \hat{p} \leq \underline{p}^t. \end{cases}$$

If $\underline{p}^t < p^*$, then any individual with a type $p \in (\underline{p}^t, p^*)$ can improve her payoff by announcing a type $\hat{p} < \underline{p}^t$ because

$$U(p, p) = v(p) < 0 = U(\hat{p}, p).$$

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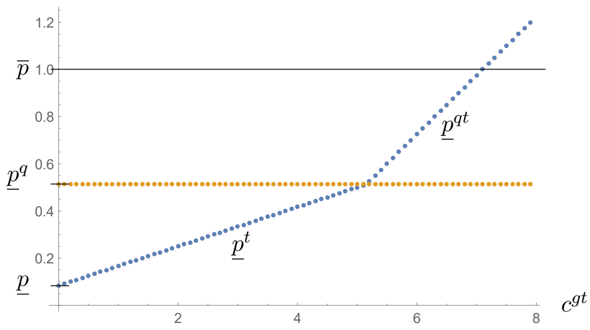


Figure 1: Example of a government's first-best optimal rule as a function of the cost of a test unit, $c^{gt}$. The blue curve given by the value of $\underline{p}^t$ or, resp., $\underline{p}^{qt}$, indicates the marginally tested type. The orange line indicates the marginally quarantined type. For this diagram, it is assumed that $w^1 = 1$, $F$ is the uniform distribution on the interval $[\underline{p}, \overline{p}] = [0.1, 1]$, $b = 8$, $c^q = 4$, $c^t = 1$, $b^q = 8$, $c^{gq} = 0.1$. The computations were performed using Mathematica 12.

By such a misrepresentation of the personal health signal, the individual avoids an unwanted test.

Similarly, if $\underline{p}^t > p^*$, then any individual with a type $p \in (p^*, \underline{p}^t)$ can improve her payoff by announcing a type $\hat{p} > \underline{p}^t$. By such a misrepresentation of the personal health signal, the individual snatches an undeserved test.

Only in the non-generic case where the parameters happen to be such that $\underline{p}^t = p^*$, it is true that the first-best solution is incentive compatible.

The described misrepresentation of the personal health signal is not possible if all types are tested (i.e., $\underline{p}^t \leq \underline{p}$) or no type is tested (i.e., $\underline{p}^t > \overline{p}$). We should mention that incentive compatibility can be violated even if the parameters are such that no type is tested. This violation happens if the first-best solution requires that some, but not all, individuals are quarantined; i.e., $\underline{p} < \underline{p}^q < \overline{p}$. Incentive compatibility fails for individuals with types above $\underline{p}^q$; they are supposed to be quarantined, but can avoid this by claiming that their type is below $\underline{p}^q$.

Our conclusion that the first best typically fails to be incentive compatible makes clear that, in order to achieve its welfare goal, the government must take the individual's incentive compatibiliy conditions into account. Our results will show that this approach leads to a rather different solution of the government's problem.

## 3 Results

In this section, we provide a general solution of the government's problem, we consider a number of important special cases, and we discuss the role of certain exogeneous parameters, that is, we consider comparative statics.

Proposition 2 is our fundamental result that describes how the government optimally combines testing and social distancing to resolve the tradeoff between

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maximizing the individual's current expected utility and curbing the spread of the disease, while taking the incentive-compatibility conditions into account.

**Proposition 2.** *It is either optimal for the government to test nobody and quarantine everybody, or the government's problem has a solution* $(m^*, q^*)$ *that takes the following form. There exists* $\check{p} \in [\underline{p}, \overline{p}]$ *such that, for all types* $p$*, the optimal testing schedule is*

$$m^*(p) \quad = \quad \begin{cases} 0 & \text{if } p < \check{p}, \\ \check{m} & \text{if } p \geq \check{p}, \end{cases}$$

*where*

$$\check{m} \quad = \quad \frac{c^q}{c^q + \max\{v(\check{p}), 0\}}. \tag{14}$$

*If* $\check{p} \leq p^*$*, then the optimal quarantining probability is*

$$q^*(p) \quad = \quad \frac{-v(\check{p})}{c^q} \quad \text{for all } p < \check{p}.$$

*If* $\check{p} > p^*$*, then the optimal quarantining probability is*

$$q^*(p) \quad = \quad 0 \quad \text{for all } p < \check{p},$$

*and*

$$q^*(p) \quad = \quad 1 \quad \text{for all } p \geq \check{p}.$$

It should come as no surprise that it can be optimal for the government to test nobody and quarantine everybody (at the considered point in time); testing nobody should be interpreted here as saving any available testing capacity for a different population of individuals or for use at another point in time. This extreme solution applies, for example, if the government puts almost zero weight on the current expected utility of the individual (i.e., $w^1 \approx 0$), and has almost zero cost of surveillance of the quarantine (i.e., $c^{gq} \approx 0$), so that, essentially, its only concern is the spread of the disease (cf. Corollary 2). The other possible form of the solution described in Proposition 2 is more interesting.

In the described optimum, there exists a fixed testing probability $\check{m}$ and a marginal type, $\check{p}$, such that an individual may be tested only if she claims to be feeling sufficiently ill (i.e., be at or above the marginal type); all individuals with types above the marginal type are tested with the same probability. Accordingly, only two different quarantining probabilities are applied in any given solution: one probability for those who claim to be of the marginal type or higher, and one for those who claim to be below. Thus, the mechanism only makes use of a binary information: in essence, it asks whether the individual feels relatively healthy (type below $\check{p}$) or rather ill (type at or above $\check{p}$).

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The quarantining probability $q^*(p)$ is designed such that, for each type $p$, an individual of type $p$ is willing to reveal her type truthfully to the mechanism. In other words, no individual has an incentive to lie about their personal health signal.

The simplest solution possibility is that the marginal type $\check{p} = p^*$, that is, $v(\check{p}) = 0$. This solution features $\check{m} = 1$, that is, the types above $p^*$ are tested for sure, whereas the types below $p^*$ are not tested at all. This is exactly what the individual would like to happen in the absence of any additional incentives. Accordingly, no social distancing is required in the optimum (i.e., $q^*(p) = 0$).

Another possibility for the optimum is that $\check{p} < p^*$, that is, the marginal type has a negative test value, $v(\check{p}) < 0$. In this case, it is still optimal to use the testing probability $\check{m} = 1$, that is, all those who feel relatively ill are tested for sure. But now there is an interval of types, from $\check{p}$ to $p^*$, who are supposed to get tested, but would refuse so in the absence of additional incentives. In order to make individuals with these types reveal themselves so they can be tested, some social distancing (i.e., $q^*(p) > 0$) is enforced for individuals who remain untested. This lowers each individual's payoff from not getting tested. Thus, an individual of type $p^*$, who would otherwise be indifferent, now strictly prefers to be tested, and so do the types in between $\check{p}$ and $p^*$. For any individual with a type $p \geq \check{p}$, the value of $q^*(p)$ is irrelevant because individuals with such types $p$ are tested for sure; in the proposition, $q^*(p)$ is specified only for the types $p < \check{p}$.

Note that, within the cases with $\check{p} < p^*$, an extreme possibility is that $\check{p} = \underline{p}$, that is, everybody is tested; the individual will be quarantined if and only if the test is positive.

The remaining possibility for the optimum is that $\check{p} > p^*$, that is, the marginal type has a positive test value, $v(\check{p}) > 0$. In this case, it is optimal to use a testing probability $\check{m} < 1$, that is, even those who feel rather ill are not tested for sure. Applying a testing probability $\check{m}$ below 1 may be interpreted as randomly selecting a fraction $\check{m}$ from the group of individuals who claim to be relatively ill and test only those. In the absence of additional incentives via quarantining, individuals with types in between $p^*$ and $\check{p}$ would pretend to be rather sick in order to snatch a test. In order to prevent this, the testing is probabilistic, that is, only a randomly selected fraction $\check{m}$ of the individuals who claim to have types above $\check{p}$ are tested, and each individual of such a type that does not belong to the tested fraction is put in quarantine for sure. Each individual now faces a gamble if she volunteers to get tested: with some probability she is then *not* tested and is *still* put in quarantine, whereas she would not have been put in quarantine had she not volunteered. Individuals with higher types are more willing than those with lower types to take such a gamble because for them the test is more valuable, while the hassle of being put in quarantine for those who do not get a test is type-independent.

Note that one possibility is that $\check{p} = \overline{p}$. Such a solution is essentially equivalent to no-testing-no-quarantining (strictly speaking, the highest type, $\overline{p}$, is tested with a positive probability, but this exact type occurs with probability 0, and the

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government may as well not test this type).

What is missing from Proposition 2 is the characterization (in terms of the exogeneous parameters of the model) of the cases in which it is optimal to test nobody and quarantine everybody, and, concerning the other cases, a characterization of the optimal threshold $\check{p}$. This gap will be closed via Proposition 3. Some auxiliary functions must be specified. These functions are defined via the exogeneous parameters of the model. For all types $p$, define

$$\begin{aligned} B(p) &= \left(-(b-c^q)w^1 p - c^{gt} - \frac{c^{gq}}{c^q}v(p)\right)F(p) \\ &\quad + \left((b-c^q)w^1 + b^q + \frac{b^q}{c^q}v(p)\right)E_{p'\sim F}[p'|p' \le p]F(p). \end{aligned} \tag{15}$$

For all $\lambda \ge 0$ and all types $p$, define

$$A^\lambda(p) = B(p) + \mathbf{1}_{p>p^*} \cdot v(p)(\lambda - \lambda^*), \tag{16}$$

where

$$\lambda^* = -w^1 + \frac{b^q E_{p'\sim F}[p'] - c^{gq}}{c^q}.$$

For all $\lambda \ge 0$, define

$$\alpha^\lambda = -\min_p A^\lambda(p) + A^0(\overline{p}) - \lambda c^q. \tag{17}$$

The following lemma implies that the function $\lambda \mapsto \alpha^\lambda$ is strictly decreasing on $[0,\infty)$, and, by the intermediate-value theorem, intersects the horizontal axis. Thus, there exists a unique $\check{\lambda}$ such that $\alpha^{\check{\lambda}} = 0$. The proof is straightforward and is relegated to the Appendix.

**Lemma 1.** *The function $\lambda \mapsto \alpha^\lambda$ is Lipschitz continuous. Its derivative satisfies the inequalities $-v(\overline{p}) - c^q \le d\alpha^\lambda/d\lambda \le -c^q$. Moreover, $\alpha^0 \ge 0$, and $\alpha^\lambda \le 0$ for all sufficiently large $\lambda$.*

The following result determines which of the solutions that are described in Proposition 2 applies. Proposition 3 not only characterizes the optimal solution, but also provides a computational path to solving the government's problem for any parameter constellation.

**Proposition 3.** *Let $\check{\lambda} \ge 0$ be such that $\alpha^{\check{\lambda}} = 0$. If $\check{\lambda} \le \lambda^*$, then the government's problem has a solution such that nobody is tested and everybody is quarantined.*

*Alternatively, suppose that $\check{\lambda} \ge \lambda^*$. Let $\check{p}$ be a minimizer of $A^{\check{\lambda}}$. Then $\check{p}$ yields a solution for the government's problem as described in Proposition 2.*

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The proof of Proposition 2 and Proposition 3 is relegated to Section 4. Examples will be provided below.

Concerning the form of the solution of the government's problem, the most fundamental distinction occurs between four different categories of solutions (cf. the explanations below Proposition 2): first, *no-testing-always-quarantining*, second, a mechanism that *sets up testing incentives* (i.e., $\check{p} < p^*$), third, *testing disincentives* (i.e., $\check{p} > p^*$), and fourth, the "null" mechanism that is characterized by the *absence of testing incentives or disincentives*, that is, the individual behavior remains unregulated (i.e., $\check{p} = p^*$).

Proposition 4 provides conditions on the model parameters that can be verified directly in order to check which of the four possibilities applies in any particular environment. In order to formulate these conditions, additional notation is needed. Let

$$\underline{B} = \min_{p \leq p^*} B(p),$$

$$\bar{l} = \frac{1}{c^q}(A^0(\overline{p}) - \underline{B}), \quad \text{and } \overline{\lambda} = \max\{0, \bar{l}\}.$$

For any $\lambda \geq 0$, define

$$\underline{A}^\lambda = \min_{p \geq p^*} A^\lambda(p).$$

Also note that, if $\lambda^* \geq 0$ and (17) is evaluated at $\lambda = \lambda^*$, then the definition simplifies to

$$\alpha^{\lambda^*} = -\min_p B(p) + B(\overline{p}) - (v(\overline{p}) + c^q)\lambda^*. \tag{18}$$

The conditions provided in Proposition 4 refer to the four numbers $\lambda^*$, $\alpha^{\lambda^*}$, $\underline{B}$, and $\underline{A}^{\overline{\lambda}}$. Computing these numbers is relatively easy: $\lambda^*$ is defined directly in terms of the exogeneous model parameters, and to compute each of the other three numbers, a single one-dimensional minimization problem must be solved. Thus, computing the four numbers is easier than fully computing the function $\lambda \mapsto \alpha^\lambda$, which would be required to apply Proposition 3 directly. On the other hand, Proposition 3 fully specifies a solution to the government's problem, whereas Proposition 4 mainly serves to characterize four different categories of solution possibilities; in particular, in Proposition 4 the exact value of $\check{p}$ is not specified in the case in which testing disincentives are optimal (i.e., $\check{p} > p^*$).

Note that, while this is not explicit from the statement, Proposition 4 allows to distinguish cases in which setting up testing incentives is optimal (i.e., $\check{p} < p^*$) from cases in which the null mechanism is optimal (i.e., $\check{p} = p^*$): if the restriction of $B$ to the interval $[\underline{p}, p^*]$ is minimized at $p^*$, then the null mechanism is optimal; if it is minimized at a point below $p^*$, setting up testing incentives is optimal.

**Proposition 4.** *If $\lambda^* \geq 0$ and $\alpha^{\lambda^*} \leq 0$, then the government's problem has a solution such that nobody is tested and everybody is quarantined.*

*Alternatively, suppose that $\lambda^* < 0$, or $\lambda^* \geq 0$ and $\alpha^{\lambda^*} > 0$. Then there exists a solution to the government's problem with marginal type $\check{p}$ as defined in Proposition 3 such that the following holds.*

*If $\underline{B} \leq \underline{A}^{\overline{\lambda}}$, then $\check{p} \in \arg\min_{p \leq p^*} B(p)$.*

*If $\underline{B} > \underline{A}^{\overline{\lambda}}$, then $\check{p} > p^*$.*

Here is a sketch of the proof. The condition for the optimality of no-testing-always-quarantining means that the strictly decreasing function $\lambda \mapsto \alpha^{\lambda}$ has already dipped below the horizontal axis when it reaches the point $\lambda = \lambda^*$. Thus, it intersects the horizontal axis to the left of the point $\lambda^*$, which corresponds to the condition on $\check{\lambda}$ given in Proposition 3. To understand where the other conditions arise, suppose for simplicity that $\bar{l} \geq 0$, that is, $\overline{\lambda} = \bar{l}$. Then

$$0 \quad = \quad -\underline{B} + A^0(\overline{p}) - \overline{\lambda} c^q,$$

that is, $\overline{\lambda}$ is the number at which we would have $\alpha^{\overline{\lambda}} = 0$ if the minimizer $\check{p}$ of $A^{\overline{\lambda}}$ belonged to $[\underline{p}, p^*]$, that is, if $\underline{B} \leq \underline{A}^{\overline{\lambda}}$. In this case, by Proposition 3, the government's problem has a solution with $\check{\lambda} = \overline{\lambda}$ and thus $\check{p} \leq p^*$. Similar arguments imply that, if the opposite inequality $\underline{B} > \underline{A}^{\overline{\lambda}}$ holds, then $\check{\lambda} > \overline{\lambda}$ and the minimizer $\check{p}$ of $A^{\check{\lambda}}$ cannot belong to $[\underline{p}, p^*]$, that is, $\check{p} > p^*$. The details of the proof of Proposition 4 are relegated to the Appendix.

Figure 2 illustrates Proposition 4. Fixing all other parameters, we consider testing costs that range from 1 to 4, and type distributions that are indexed by a parameter $\beta$ that ranges from 0.1 to 1.5. Specifically, we assume that the lowest type $\underline{p} = 0.1$, the highest type $\overline{p} = 1$, and consider the distribution

$$F(p) = \left( \frac{p - \underline{p}}{\overline{p} - \underline{p}} \right)^{\beta}.$$

This specification is meant to capture that, the larger $\beta$, the more ill is the population, that is, the more probability mass is shifted to higher types.

Each blue dot in Figure 2 represents a pair $(c^{gt}, \beta)$ such that no regulation is optimal (i.e., $\check{p} = p^*$); each orange dot represents a pair $(c^{gt}, \beta)$ such that it is optimal to test more than in the absence of regulation, that is, setting up testing incentives is optimal (i.e., $\check{p} < p^*$); each blue dot represents a pair $(c^{gt}, \beta)$ such that it is optimal to test less than in the absence of regulation, that is, setting up testing disincentives is optimal (i.e., $\check{p} > p^*$). Naturally, the more ill is the population (i.e., the higher is $\beta$), the larger is the range of testing-cost levels $c^{gt}$ such that setting up testing incentives is optimal, and the smaller is the range of testing-cost parameters such that setting up testing disincentives is optimal.

In order to provide more insight into the nature of the solution of the government's problem, we now present a number of special cases.

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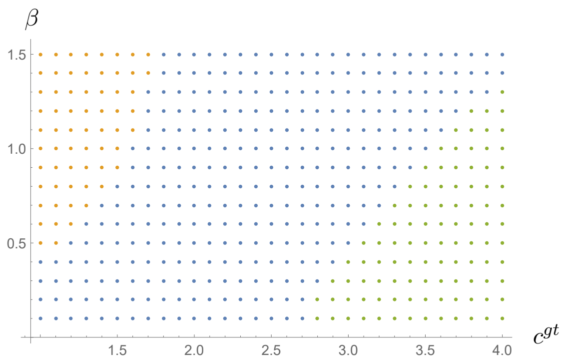


Figure 2: Examples of parameter constellations such that setting up testing incentives is optimal (orange dots), leaving behavior unregulated is optimal (blue dots), and setting up testing disincentives is optimal (green dots). For this diagram, it is assumed that $w^1 = 1$, $\overline{p} = 1$, $\underline{p} = 0.1$, $F(p) = ((p - \underline{p})/(\overline{p} - \underline{p}))^\beta$, $b = 8$, $c^q = 4$, $c^t = 1$, $b^q = 8$, $c^{gq} = 0.1$. Consequently, $p^* = 0.25$. Each orange dot represents a pair $(c^{gt}, \beta)$ such that $\check{p} < p^*$; each blue dot represents a pair $(c^{gt}, \beta)$ such that $\check{p} = p^*$; each green dot represents a pair $(c^{gt}, \beta)$ such that $\check{p} > p^*$. The computations were performed using Mathematica 12.

**Special cases and comparative statics**

First of all, we have the following benchmark:

**Corollary 1.** *If, for given values of the other parameters, the public cost and benefit parameters $c^{gt}$, $c^{gq}$, and $b^q$, are sufficiently close to 0, then $\check{p} = p^*$, that is, it is optimal to leave the individual behavior unregulated.*

The benchmark considered here is a situation in which the spread of the disease is considered almost irrelevant, so that the individual's current expected utility is essentially the only important design aspect. The government's motivation for any regulation is the externality of the individual's behavior concerning the spread of the disease. If this motivation ceases to be relevant, the optimum is the null contract.

To obtain a heuristic argument towards the proof, consider the hypothetical limit case $c^{gt} = c^{gq} = b^q = 0$. By definition of $\lambda^*$, we have $\lambda^* = -w^1 < 0$. Hence, by Proposition 3 there exists a solution with a marginal type $\check{p}$.

Also note that (15) implies that

$$B(p) \quad = \quad (b - c^q)w^1 E_{p' \sim F}[\mathbf{1}_{p' \leq p} \cdot (-p + p')],$$

which has the slope

$$B'(p) \quad = \quad -(b - c^q)w^1 F(p) \ < \ 0,$$

implying that $B$ is strictly decreasing.

On the other hand, (16) together with $\lambda^* = -w^1$ implies that, for all $p > p^*$ and all $\lambda \geq 0$,

$$A^\lambda(p) \quad = \quad B(p) + v(p)(\lambda + w^1),$$

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which has the slope

$$(A^{\lambda})'(p) \quad = \quad B'(p) + (b - c^q)(\lambda + w^1) \;\geq\; (b - c^q)w^1(1 - F(p)) \;>\; 0,$$

implying that $A^{\lambda}$ is strictly increasing for all $p \geq p^*$.

We conclude that $A^{\lambda}$, and in particular $A^{\check{\lambda}}$, is minimized at $p^*$, showing that $\check{p} = p^*$ by Proposition 3. The arguments above are easily extended to the case in which the parameters $c^{gt}$, $c^{gq}$, and $b^q$ are not exactly equal to 0, but are sufficiently close to 0; the details are omitted.

Note that, according to the first-best solution described in Proposition 1, if the public cost and benefit parameters $c^{gt}$, $c^{gq}$, and $b^q$ are close to 0, but not exactly equal to 0, then, generically, $\underline{p}^t \neq p^*$. In these cases, the first-best solution differs from the null mechanism while the null mechanism is still second-best optimal, as shown in Corollary 1. In other words, while the omniscient and omnipotent government's optimal rule reacts with stipulating some regulation to even the slighest concern about public costs and benefits, a government that must take the incentive constraints into account optimally sticks to the null mechanism if public costs and benefits are small.

Next we consider the opposite extreme case where the government does not care much about the individual's current expected utility, that is, $w^1$ is close to 0 and, in addition, the quarantine can be enforced at almost zero cost.

**Corollary 2.** *If, for given values of the other parameters, $w^1$ and $c^{gq}$ are sufficiently close to 0, then testing nobody and quarantining everybody is optimal.*

Again, we obtain a heuristic argument towards the proof by considering the hypothetical limit case where $w^1 = 0$ and $c^{gq} = 0$. By definition,

$$\lambda^* \quad = \quad \frac{b^q}{c^q} E[p'] > 0$$

and

$$B(p) \quad = \quad \left(-c^{gt}\right) F(p) + \left(b^q + \frac{b^q}{c^q} v(p)\right) E[p'|p' \leq p] F(p). \tag{19}$$

In particular,

$$B(\overline{p}) = -c^{gt} + \left(b^q + \frac{b^q}{c^q} v(\overline{p})\right) E[p'] = -c^{gt} + (c^q + v(\overline{p}))\lambda^*.$$

Thus, using (18),

$$\alpha^{\lambda^*} = -\min_p B(p) - c^{gt} = -\min_p (B(p) + c^{gt}). \tag{20}$$

Note also that $v(p) \geq -c^t \geq -c^q$, implying $v(p)/c^q + 1 \geq 0$. Hence,

$$b^q + \frac{b^q}{c^q} v(p) \quad \geq \quad 0. \tag{21}$$

This together with (19) implies that $B(p)+c^{gt} \geq 0$. Thus, (20) implies that $\alpha^{\lambda^*} \leq 0$. Thus, testing nobody and quarantining everybody is optimal by Proposition 4. Combining the above arguments with appropriate continuity arguments leads to the proof of Corollary 2; the details are relegated to the Appendix.

Next we consider comparative statics with respect to the government's cost of testing the individual, $c^{gt}$. We distinguish the case in which the current individual utility is relatively important (i.e., $w^1$ above a threshold) and the opposite case where curbing the spread of the disease is considered relatively more important (i.e., $w^1$ below the threshold). In the first case, the marginally tested type $\check{p}$ is increasing in the cost $c^{gt}$ until a cost level $\bar{c}^{gt}$ is reached at which no-testing-*no*-quarantining is optimal; this remains the solution at all higher cost levels.

In the remaining oppositive case where the current individual utility is less important (i.e., $w^1$ below the threshold), the marginally tested type is increasing in the cost $c^{gt}$ until a cost level $\bar{c}^{gt}$ is reached at which no-testing-*always*-quarantining is optimal; this remains the solution at all higher cost levels.

**Corollary 3.** *(Comparative statics with respect to $c^{gt}$, keeping the other parameters fixed.)*

*Consider the case $w^1 \geq \frac{b^q E_{p' \sim F}[p'] - c^{gq}}{c^q}$. Then there exists a marginally tested type $\check{p}$. Moreover, choosing either the minimal or the maximal $\check{p}$ in case of multiplicity, $\check{p}$ is weakly increasing in $c^{gt}$, and $\check{p} \to \overline{p}$ as $c^{gt} \to \infty$.*

*Consider the case $w^1 < \frac{b^q E_{p' \sim F}[p'] - c^{gq}}{c^q}$. Then there exists a threshold $\bar{c}^{gt}$ such that, for all $c^{gt} < \bar{c}^{gt}$, the marginally tested type $\check{p}$ (choose the minimal or maximal $\check{p}$ in case of multiplicity) is weakly increasing in $c^{gt}$; no-testing-always-quarantining is optimal for all $c^{gt} \geq \bar{c}^{gt}$.*

The proof of Corollary 3 is relegated to the Appendix. Figure 3 illustrates the case $w^1 < (b^q E_{p' \sim F}[p'] - c^{gq})/c^q$ in Corollary 3. In this example, $p^* = 0.25$. If the testing cost $c^{gt}$ is small, it is optimal to test everybody, that is $\check{p} = \underline{p}$. Then there is a range of testing costs in which it is optimal to set up testing incentives, but not everybody is tested, that is, $\underline{p} < \check{p} < p^*$. This is followed by a range of testing costs such that the null mechanism is optimal. If the testing cost is even higher, it becomes optimal to provide ever stronger testing disincentives. At the point $\bar{c}^{gt} \approx 9.4$, testing capacity is is so scarce that no-testing-always-quarantine is optimal if the cost is even higher.

Note that the second-best solution is strikingly different from of the first-best solution at the same parameters that was illustrated in Figure 1. At low testing costs ($c^{gt}$ below $\approx 5.1$), the first best relies on testing some types without extra quarantining of untested types; such a solution violates incentive compatibility and thus is not feasible; in the second best, type-revelation incentives are provided via social-distancing of untested types or randomized testing, and this also changes the optimal testing schedule relative to the first best.

At very high testing costs ($c^{gt}$ above $\approx 7.1$), since testing is now very expensive, tests are not applied at all in the first-best solution—the first best then

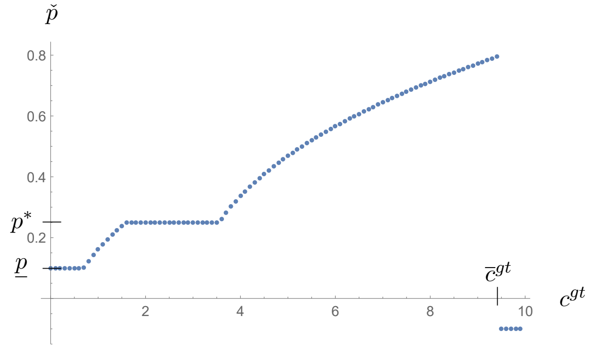


Figure 3: Example of a government's second-best optimal marginally tested type, $\check{p}$, as a function of the government's cost of a test unit, $c^{gt}$. The cases in which $c^{gt} > \overline{c}^{gt}$, where no-testing-always-quarantining is optimal, are represented via a negative value of $\check{p}$. For this diagram, it is assumed that $w^1 = 1$, $F$ is the uniform distribution on the interval $[\underline{p}, \overline{p}] = [0.1, 1]$, $b = 8$, $c^q = 4$, $c^t = 1$, $b^q = 8$, $c^{gq} = 0.1$. The computations were performed using Mathematica 12.

relies entirely on quarantining of individuals with sufficiently high types, which again violates incentive compatibility and thus is not feasible; in the second best, some tests are still applied, in an incentive-compatible way, until the testing cost is so high that the government gives up on testing and resorts to quarantining everybody.

Figure 4 illustrates the case $w^1 > (b^q E_{p' \sim F}[p'] - c^{gq})/c^q$ in Corollary 3. This case is reached because now we assume that $\underline{p} = 0.0001$—some types are almost sure to not be infected. These types remain untested even if the testing cost $c^{gt}$ is very close to zero, implying that $\check{p}$ is strictly increasing essentially from the start. As in the previous example, there is a range of testing costs such that the null mechanism is optimal, and if testing cost are even higher, it becomes optimal to provide ever stronger testing disincentives. In contrast to the previous example, however, no-testing-no-quarantining is optimal if testing capacities are sufficiently scarce.

## 4 Proof of Proposition 2 and Proposition 3

As a first step, we rewrite the government's problem as a convex maximization problem over testing schedules $m(\cdot)$. As a second step, we show that the solution $m^*(\cdot)$ described in Proposition 2 and Proposition 3 satisfies the (Lagrangian first-order) sufficient conditions for solving the problem as rewritten in the first step. As a third step, we show that the optimal quarantining schedule $q^*(\cdot)$ described in Proposition 2 and Proposition 3 is a consequence of the optimal testing schedule $m^*(\cdot)$.

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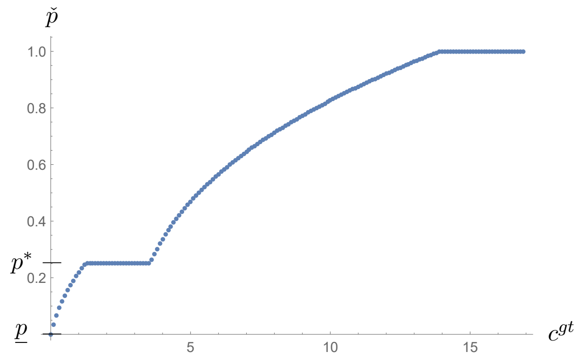


Figure 4: Example of the government's second-best optimal marginally tested type, $\check{p}$, as a function of the government's cost of a test unit, $c^{gt}$. If the testing cost is sufficiently high, then $\check{p} = \overline{p}$, that is, no-testing-no-quarantining is optimal. For this diagram, it is assumed that $w^1 = 1$, $F$ is the uniform distribution on the interval $[\underline{p}, \overline{p}] = [0.0001, 1]$, $b = 8$, $c^q = 4$, $c^t = 1$, $b^q = 8$, $c^{gq} = 0.1$. The computations were performed using Mathematica 12.

**Step 1: rewriting the government's problem**

Using standard techniques from mechanism design (see, e.g., Börgers (2015), Chapter 3), we have the following result.

**Lemma 2.** *A rule $(m, q)$ is incentive compatible if and only if*

$$U(p,p) = (b - c^q)\int_{\underline{p}}^{p} m(p')dp' + U(\underline{p},\underline{p}) \quad \textit{for all } p, \tag{22}$$

*and*

$$m(p) \leq m(p') \quad \textit{for all } p < p' \tag{23}$$

The first condition (22) is an envelope or integrability condition that yields a "revenue-equivalence" result: the testing schedule $m(\cdot)$ determines the individual's expected utility as a function of the type, up to the constant $U(\underline{p},\underline{p})$. Thus, by equating the integrability condition with the individual utility expression (6), we get, for each type $p$, a condition for the quarantine probability $q(p)$ such that the integrability condition is satisfied:

$$v(p)m(p) - c^q(1 - m(p))q(p) \quad = \quad (b - c^q)\int_{\underline{p}}^{p} m(p')dp' + U(\underline{p},\underline{p}).$$

Rearranging, we can express the joint probability of remaining untested and being quarantined:

$$(1 - m(p))q(p) \quad = \quad \underbrace{\frac{1}{c^q}\left(v(p)m(p) - (b - c^q)\int_{\underline{p}}^{p} m(p')dp' - U(\underline{p},\underline{p})\right)}_{\equiv\, \psi^{U(\underline{p},\underline{p}),m}(p)}. \tag{24}$$

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Now consider a testing schedule $m(\cdot)$ that satisfies the monotonicity condition (23) and the probability condition (4).

We would like to characterize the set of $m(\cdot)$ such that $(m, q)$ is incentive compatible for some quarantining schedule $q(\cdot)$. Given some $m(\cdot)$, the question is then whether or not there exists $q(\cdot)$ that satisfies the probability condition (5) together with the equation (24), where (setting $\hat{p} = p = \underline{p}$ in (6))

$$U(\underline{p}, \underline{p}) \quad = \quad v(\underline{p})m(\underline{p}) - c^q(1 - m(\underline{p}))q(\underline{p}).$$

Note that this last equation already follows from (24) as applied with $p = \underline{p}$. Thus, we can treat the number $U(\underline{p}, \underline{p})$ as a variable that can take any value that satisfies (24).

Multiplying (5) with $1 - m(q)$, we obtain the essentially equivalent condition

$$0 \leq (1 - m(p))q(p) \leq 1 - m(p) \quad \text{for all } p, \tag{25}$$

(Note that this condition, in contrast to (5), leaves $q(p)$ undetermined if $m(p) = 1$; this change, however, is inessential because the quarantining probability $q(p)$ is irrelevant for an individual who is tested for sure.)

Plugging (24) into (25), we obtain a condition on $m(\cdot)$ that is necessary and sufficient for the existence of a $q(\cdot)$ such that $(m, q)$ is incentive compatible:

$$0 \leq \psi^{U(\underline{p},\underline{p}),m}(p) \leq 1 - m(p) \quad \text{for all } p, \tag{26}$$

The next step is to express the welfare $W$ as a function of the testing schedule $m(\cdot)$ and the number $U(\underline{p}, \underline{p})$. This is achieved by plugging into (8) the expressions obtained in (22) and (24), giving

$$\begin{aligned} W \quad = \quad & E_{p\sim F}\left[w^1\left((b - c^q)\int_{\underline{p}}^{p} m(p')dp' + U(\underline{p}, \underline{p})\right)\right. \\ & \left. + b^q p\left(m(p) + \psi^{U(\underline{p},\underline{p}),m}(p)\right) - c^{gt}m(p) - c^{gq}\psi^{U(\underline{p},\underline{p}),m}(p)\right]. \end{aligned} \tag{27}$$

The government's goal is to solve the following problem:

$$\begin{aligned} & \max_{U(\underline{p},\underline{p}),\ m(\cdot)} W \\ \text{s.t.} \quad & (4), \quad (23), \quad (26) \end{aligned}$$

The left condition in (26) is satisfied for all $p$ if and only if it is satisfied for the $p$ that minimizes the function $\psi^{U(\underline{p},\underline{p}),m}(p)$. The minimizer is $p = p^*$; to see this, consider any $p \neq p^*$ and note that[16]

$$
\begin{aligned}
&\left(\psi^{U(\underline{p},\underline{p}),m}(p) - \psi^{U(\underline{p},\underline{p}),m}(p^*)\right) c^q \\
&= v(p)m(p) - (b-c^q)\int_{p^*}^{p} m(p')dp' \\
&= (b-c^q)(p-p^*)m(p) - (b-c^q)\int_{p^*}^{p} m(p')dp'.
\end{aligned}
$$

Due to (23), the last integral is bounded above by $(p-p^*)m(p)$, showing that $\psi(p) \geq \psi(p^*)$.

Thus we can replace the left condition in (26) by the simpler condition $0 \leq \psi^{U(\underline{p},\underline{p}),m}(p^*)$ or, equivalently, using (24), by the condition

$$
U(\underline{p},\underline{p}) \quad \leq \quad -(b-c^q)\int_{\underline{p}}^{p^*} m(p')dp'. \tag{28}
$$

The right condition in (26) is satisfied for all $p$ if and only if it is satisfied for the $p$ that maximizes the function $\psi^{U(\underline{p},\underline{p}),m}(p) + m(p)$. The maximizer is $p = \overline{p}$; to see this, consider any $p < \overline{p}$ and note that

$$
\begin{aligned}
&\left(\psi^{U(\underline{p},\underline{p}),m}(\overline{p}) + m(\overline{p}) - \psi^{U(\underline{p},\underline{p}),m}(p) - m(p)\right) c^q \\
&= (v(\overline{p})+c^q)m(\overline{p}) - (v(p)+c^q)m(p) - (b-c^q)\underbrace{\int_{p}^{\overline{p}} m(p')dp'}_{\leq(\overline{p}-p)m(\overline{p}) \text{ by (23)}}.
\end{aligned}
$$

Due to (1), $v(p)+c^q > 0$. Thus, again using that $m(p) \leq m(\overline{p})$ from (23), we can continue the above equation via the estimation

$$
\begin{aligned}
&\geq (v(\overline{p})+c^q)m(\overline{p}) - (v(p)+c^q)m(\overline{p}) - (b-c^q)(\overline{p}-p)m(\overline{p}) \\
&= (v(\overline{p})-v(p))m(\overline{p}) - (b-c^q)(\overline{p}-p)m(\overline{p}) \\
&= 0,
\end{aligned}
$$

where the last equality relies on the definition of $v$ in (2).

Thus, we can replace the right condition in (26) by the simpler condition $\psi^{U(\underline{p},\underline{p}),m}(\overline{p}) \leq 1 - m(\overline{p})$ or, equivalently, using (24), by the condition

$$
(v(\overline{p})+c^q)m(\overline{p}) - (b-c^q)\int_{\underline{p}}^{\overline{p}} m(p')dp' - c^q \quad \leq \quad U(\underline{p},\underline{p}). \tag{29}
$$

At this point, it is useful to take stock: we have replaced the condition (26), which is required for all $p$, by two one-dimensional conditions: (28) provides an upper bound for $U(\underline{p},\underline{p})$, and (29) provides a lower bound for $U(\underline{p},\underline{p})$.

[16] By convention, an integral $\int_{p^*}^{p} \ldots$ with $p^* > p$ is equal to $-\int_{p}^{p^*} \ldots$.

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The first step towards solving the government's problem is to eliminate the variable $U(\underline{p},\underline{p})$.

According to (24) and (27), the government's objective $W$ is linear with respect to $U(\underline{p},\underline{p})$, with slope

$$w^1 - \frac{b^q E_{p\sim F}[p] - c^{gq}}{c^q} \quad = \quad -\lambda^*.$$

In the following computations, we have to distinguish two cases, depending on the sign of $\lambda^*$. Suppose first that

$$\lambda^* \quad \leq \quad 0. \tag{30}$$

Then $W$ is weakly increasing in $U(\underline{p},\underline{p})$. Thus, there exists an optimal $U(\underline{p},\underline{p})$ that hits the upper bound provided by (28), that is,

$$U(\underline{p},\underline{p}) \quad = \quad -(b-c^q)\int_{\underline{p}}^{p^*} m(p')dp'. \tag{31}$$

Plugging (31) into (29), we have

$$(v(\overline{p})+c^q)m(\overline{p}) - (b-c^q)\int_{\underline{p}}^{\overline{p}} m(p')dp' - c^q \quad \leq \quad -(b-c^q)\int_{\underline{p}}^{p^*} m(p')dp'.$$

This (one-dimensional) condition replaces (26) in the government's optimization. Rearranging, we obtain the equivalent condition

$$(v(\overline{p})+c^q)m(\overline{p}) - (b-c^q)\int_{p^*}^{\overline{p}} m(p')dp' \quad \leq \quad c^q. \tag{32}$$

Next we rewrite the welfare $W$ by plugging into (27) the expression for $U(\underline{p},\underline{p})$ that was obtained in (31):

$$\begin{aligned} W \quad = \quad & E_{p\sim F}\Bigg[w^1(b-c^q)\int_{p^*}^{p} m(p')dp' \\ & + (b^q p - c^{gt})m(p) + (b^q p - c^{gq})\psi^{U(\underline{p},\underline{p}),m}(p)\Bigg]. \end{aligned}$$

Similarly, $U(\underline{p},\underline{p})$ can be substituted on the right-hand side of (24), yielding

$$\psi^{U(\underline{p},\underline{p}),m}(p) \quad = \quad \frac{1}{c^q}\left(v(p)m(p) - (b-c^q)\int_{p^*}^{p} m(p')dp'\right). \tag{33}$$

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In summary, we obtain the expression

$$\begin{aligned}
W &= E_{p\sim F}\left[w^1(b-c^q)\int_{p^*}^{p} m(p')dp' \right.\\
&\qquad \left. + (b^q p - c^{gt})m(p) + (b^q p - c^{gq})\frac{1}{c^q}\left(v(p)m(p) - (b-c^q)\int_{p^*}^{p} m(p')dp'\right)\right]\\
&= E_{p\sim F}\left[\left(w^1(b-c^q) - \frac{b^q p - c^{gq}}{c^q}(b-c^q)\right)\int_{p^*}^{p} m(p')dp'\right]\\
&\quad + E_{p\sim F}\left[\left(b^q p - c^{gt} + \frac{b^q p - c^{gq}}{c^q}v(p)\right)m(p)\right]\\
&= -\int_{\underline{p}}^{\overline{p}}\int_{p^*}^{p}(b-c^q)\kappa(p)m(p')dp'dp \ + \int_{\underline{p}}^{\overline{p}} L(p)m(p)dp, \qquad (34)
\end{aligned}$$

where we have used the auxiliary functions

$$\kappa(p) = \left(-w^1 + \frac{b^q p - c^{gq}}{c^q}\right)f(p) \qquad (35)$$

$$\text{and} \quad L(p) = \left(b^q p - c^{gt} + \frac{b^q p - c^{gq}}{c^q}v(p)\right)f(p). \qquad (36)$$

The first of the two terms in (34) can be rewritten into a more useful form. To do this, we split it into two integrals:

$$-\int_{\underline{p}}^{\overline{p}}\int_{p^*}^{p} m(p')\kappa(p)dp'dp = \int_{\underline{p}}^{p^*}\int_{p}^{p^*} m(p')\kappa(p)dp'dp - \int_{p^*}^{\overline{p}}\int_{p^*}^{p} m(p')\kappa(p)dp'dp.$$

Each of these double integrals can be simplified via changing the order of integration.

$$\int_{\underline{p}}^{p^*}\int_{p}^{p^*} m(p')\kappa(p)dp'dp = \int_{\underline{p}}^{p^*}\int_{\underline{p}}^{p'} m(p')\kappa(p)dpdp' = \int_{\underline{p}}^{p^*} K(p')m(p')dp',$$

where we have used the auxiliary function

$$K(p) = \int_{\underline{p}}^{p}\kappa(p')dp' \qquad (37)$$

Similarly, the second integral can be written as

$$-\int_{p^*}^{\overline{p}}\int_{p^*}^{p} m(p')\kappa(p)dp'dp = -\int_{p^*}^{\overline{p}}\int_{p'}^{\overline{p}} m(p')\kappa(p)dpdp' = \int_{p^*}^{\overline{p}}(K(p')-K(\overline{p}))m(p')dp'.$$

Summing up,

$$-\int_{\underline{p}}^{\overline{p}}\int_{p^*}^{p} m(p')\kappa(p)dp'dp = \int_{\underline{p}}^{\overline{p}}\left(K(p') - \mathbf{1}_{p\geq p^*}\cdot K(\overline{p})\right)m(p')dp'.$$

Note that

$$K(\overline{p}) \quad = \quad \lambda^*.$$

Thus, (34) has been simplified as

$$W \quad = \quad \int_{\underline{p}}^{\overline{p}} \left((b - c^q)K(p) + L(p) - \mathbf{1}_{p \geq p^*} \cdot (b - c^q)\lambda^*\right) m(p)dp. \tag{38}$$

So far we have achieved the following reformulation of the government's problem

$$\begin{array}{lcl} (\text{case } \lambda^* \leq 0) & & \max\limits_{m(\cdot)} \ (38) \\ & \text{s.t.} & (4), \quad (23), \quad (32). \end{array}$$

We can use, e.g., the space $PC[\underline{p}, \overline{p}]$ of piecewise continuous and right-continuous functions for the testing schedules $m(\cdot)$; this is a linear vector space. The constraints (23) and (4) define a convex subset $\Omega$ of $PC[\underline{p}, \overline{p}]$. Then the government's problem can be written as

$$\begin{array}{lcl} (\text{case } \lambda^* \leq 0) & & \max\limits_{m(\cdot) \in \Omega} \ (38) \\ & \text{s.t.} & (32). \end{array}$$

Now suppose that

$$\lambda^* \quad \geq \quad 0. \tag{39}$$

Then the government's objective $W$ is weakly decreasing in $U(\underline{p}, \underline{p})$. Hence, it is optimal to choose $U(\underline{p}, \underline{p})$ such that it hits the lower bound provided by (29), that is,

$$U(\underline{p}, \underline{p}) \quad = \quad (v(\overline{p}) + c^q)m(\overline{p}) - (b - c^q) \int_{\underline{p}}^{\overline{p}} m(p')dp' - c^q. \tag{40}$$

Plugging (40) into (28) yields the same constraint (32) that we obtained when we plugged (31) into (29).

Recall that the (one-dimensional) condition (32) replaces (26) in the government's optimization.

Next we rewrite the welfare $W$ by plugging into (27) the expression for $U(\underline{p}, \underline{p})$ that was obtained in (40):

$$\begin{aligned} W \quad = \quad & E_{p \sim F} \left[ w^1 \left( -(b - c^q) \int_{p}^{\overline{p}} m(p')dp' + (v(\overline{p}) + c^q)m(\overline{p}) - c^q \right) \right. \\ & \left. + b^q p \left( m(p) + \psi^{U(\underline{p}, \underline{p}), m}(p) \right) - c^{gt} m(p) - c^{gq} \psi^{U(\underline{p}, \underline{p}), m}(p) \right]. \end{aligned}$$

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Similarly, $U(\underline{p},\underline{p})$ can be substituted on the right-hand side of (24), yielding

$$\psi^{U(\underline{p},\underline{p}),m}(p) = \frac{1}{c^q}\left(v(p)m(p) + (b-c^q)\int_p^{\overline{p}} m(p')dp' - (v(\overline{p})+c^q)m(\overline{p})\right) + 1. \tag{41}$$

In summary, we obtain the expression

$$\begin{aligned}
W &= E_{p\sim F}\Bigg[w^1\left(-(b-c^q)\int_p^{\overline{p}} m(p')dp' + (v(\overline{p})+c^q)m(\overline{p}) - c^q\right) \\
&\quad +(b^q p - c^{gt})m(p) \\
&\quad +\frac{b^q p - c^{gq}}{c^q}\left(v(p)m(p) + (b-c^q)\int_p^{\overline{p}} m(p')dp' - (v(\overline{p})+c^q)m(\overline{p})\right) \\
&\quad + b^q p - c^{gq}\Bigg]. \\
&= E_{p\sim F}\Bigg[\left(-w^1 + \frac{b^q p - c^{gq}}{c^q}\right)(b-c^q)\int_p^{\overline{p}} m(p')dp' \\
&\quad + \left(b^q p - c^{gt} + \frac{b^q p - c^{gq}}{c^q} v(p)\right) m(p) \\
&\quad + \left(w^1 - \frac{b^q p - c^{gq}}{c^q}\right)(v(\overline{p})+c^q)m(\overline{p}) \\
&\quad - w^1 c^q + b^q p - c^{gq}\Bigg] \\
&= \int_{\underline{p}}^{\overline{p}} \Bigg(\kappa(p)(b-c^q)\int_p^{\overline{p}} m(p')dp' \ + \ L(p)m(p) \\
&\qquad - \kappa(p)(v(\overline{p})+c^q)m(\overline{p}) + \kappa(p)c^q\Bigg)\, dp,
\end{aligned} \tag{42}$$

where we have used the functions defined in (35) and (36).

The first of the four terms in (42) can be rewritten into a more useful form. The double integral can be simplified via changing the order of integration.

$$\int_{\underline{p}}^{\overline{p}}\int_p^{\overline{p}} m(p')\kappa(p)dp'dp = \int_{\underline{p}}^{\overline{p}}\int_{\underline{p}}^{p'} m(p')\kappa(p)dpdp' = \int_{\underline{p}}^{\overline{p}} K(p')m(p')dp',$$

where we have used the function $K$ defined in (37). Thus, (42) can be written as

$$W = \int_{\underline{p}}^{\overline{p}} \left((b-c^q)K(p) + L(p)\right) m(p)dp - K(\overline{p})\left((v(\overline{p})+c^q)m(\overline{p}) - c^q\right). \tag{43}$$

So far we have achieved the following reformulation of the government's problem:

$$\text{(case } \lambda^* \geq 0) \qquad \max_{m(\cdot)} (43)$$
$$\text{s.t.} \qquad (4), \quad (23), \quad (32).$$

Analogously to the earlier case $\lambda^* \leq 0$, the government's problem can also be written as

$$\text{(case } \lambda^* \geq 0) \qquad \max_{m(\cdot)\in\Omega} (43)$$
$$\text{s.t.} \qquad (32).$$

**Step 2: solving the rewritten problem**

We will now show that the solution $m^*$ described in Proposition 2 and Proposition 3 solves the government's problem as reformulated in *Step 1*.

As in Step 1, we distinguish two cases depending on the sign of $\lambda^*$. Suppose first that $\lambda^* \leq 0$.

Consider the reformulated problem from *Step 1* (case $\lambda^* \leq 0$). The following two Lagrangian conditions are sufficient for a solution (see, e.g., Luenberger (1968), Chapter 8). First, there exists a number $\lambda \geq 0$ ("Lagrange multiplier") such that $m^*(\cdot)$ solves the problem

$$\max_{m(\cdot)\in\Omega} \int_{\underline{p}}^{\overline{p}} \left((b-c^q)K(p) + L(p) - \mathbf{1}_{p\geq p^*} \cdot (b-c^q)\lambda^*\right) m(p)dp$$
$$- \lambda\left((v(\overline{p}) + c^q)m(\overline{p}) - (b-c^q)\int_{p^*}^{\overline{p}} m(p')dp'\right). \tag{44}$$

Second, (32) is satisfied with equality at $m = m^*$.

In order to show that $m^*$ satisfies these conditions, we begin by rewriting the objective of the Lagrangian problem (44):

$$W^\lambda = \int_{\underline{p}}^{\overline{p}} \overbrace{\left((b-c^q)K(p) + L(p) + \mathbf{1}_{p\geq p^*} \cdot (b-c^q)(\lambda-\lambda^*)\right)}^{\equiv a^\lambda(p)} m(p)dp$$
$$-\lambda(v(\overline{p}) + c^q)m(\overline{p}). \tag{45}$$

In order to rewrite $W^\lambda$, we introduce additional notation. For any type $p$, define the conditional expectations

$$\eta(p) = E_{p'\sim F}[p'|p' \leq p],$$
$$\eta_2(p) = E_{p'\sim F}[(p')^2|p' \leq p].$$

Thus, using integration by parts,

$$\int_{\underline{p}}^{p} F(p')dp' = -\int_{\underline{p}}^{p} p'f(p')dp' + pF(p) = (p-\eta(p))F(p). \tag{46}$$

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Similarly,

$$\int_{\underline{p}}^{p}\int_{\underline{p}}^{p'} f(p'')dp''dp' = -\int_{\underline{p}}^{p}(p')^2 f(p')dp' + p\int_{\underline{p}}^{p} f(p'')dp'' \tag{47}$$

$$= (p\eta(p) - \eta_2(p))F(p). \tag{48}$$

Using (35) and (37),

$$K(p) = -\left(w^1 + \frac{c^{gq}}{c^q}\right)F(p) + \frac{b^q}{c^q}\int_{\underline{p}}^{p} p' f(p')dp'.$$

Thus, using (46) and (48),

$$\int_{\underline{p}}^{p} K(p')dp' = -\left(w^1 + \frac{c^{gq}}{c^q}\right)(p - \eta(p))F(p) + \frac{b^q}{c^q}(p\eta(p) - \eta_2(p))F(p).$$

Using the definition (36),

$$\begin{aligned} L(p) &= \left(-c^{gt} + \frac{c^{gq}}{c^q}c^t\right)f(p) + \left(b^q - \frac{b^q}{c^q}c^t - \frac{c^{gq}}{c^q}(b - c^q)\right)pf(p) \\ &\quad + \frac{b^q}{c^q}(b - c^q)p^2 f(p). \end{aligned}$$

Thus,

$$\begin{aligned} \int_{\underline{p}}^{p} L(p')dp' &= \left(-c^{gt} + \frac{c^{gq}}{c^q}c^t\right)F(p) + \left(b^q - \frac{b^q}{c^q}c^t - \frac{c^{gq}}{c^q}(b - c^q)\right)\eta(p)F(p) \\ &\quad + \frac{b^q}{c^q}(b - c^q)\eta_2(p)F(p). \end{aligned} \tag{49}$$

Combining the derived expressions,

$$\begin{aligned} \int_{\underline{p}}^{p}\left((b - c^q)K(p') + L(p')\right)dp' &= \left(-(b - c^q)\left(w^1 + \frac{c^{gq}}{c^q}\right)p - c^{gt} + \frac{c^{gq}}{c^q}c^t\right)F(p) \\ &\quad + \left((b - c^q)\left(w^1 + \frac{b^q}{c^q}p\right) + b^q - \frac{b^q}{c^q}c^t\right)\eta(p)F(p) \\ &= \left(-(b - c^q)w^1 p - c^{gt} - \frac{c^{gq}}{c^q}v(p)\right)F(p) \\ &\quad + \left((b - c^q)w^1 + b^q + \frac{b^q}{c^q}v(p)\right)\eta(p)F(p) \\ &= B(p). \end{aligned}$$

where we have used the definition (15). Thus, by definition of the function $a^\lambda$,

$$\begin{aligned} \int_{\underline{p}}^{p} a^\lambda(p')dp' &= \int_{\underline{p}}^{p}\left((b - c^q)K(p') + L(p') + \mathbf{1}_{p' \geq p^*} \cdot (b - c^q)(\lambda - \lambda^*)\right)dp' \\ &= B(p) + \mathbf{1}_{p \geq p^*} \cdot \underbrace{(b - c^q)(p - p^*)}_{= v(p) \text{ by } (3)}(\lambda - \lambda^*) \\ &= A^\lambda(p), \end{aligned}$$

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where the last equality follows from (16).

With this in mind, we apply integration by parts to the right-hand side of (45), yielding

$$W^\lambda = -\int_{\underline{p}}^{\overline{p}} A^\lambda(p)dm(p) + A^\lambda(\overline{p})m(\overline{p}) - \lambda(v(\overline{p}) + c^q)m(\overline{p}),$$

where $m$ is interpreted as a c.d.f..

Note that, using the definition (16),

$$A^\lambda(\overline{p}) = B(\overline{p}) + v(\overline{p})(\lambda - \lambda^*).$$

Thus, we obtain the simplified formula

$$\begin{aligned} W^\lambda &= -\int_{\underline{p}}^{\overline{p}} A^\lambda(p)dm(p) + (B(\overline{p}) - v(\overline{p})\lambda^* - \lambda c^q)\, m(\overline{p}) \\ &= -\int_{\underline{p}}^{\overline{p}} A^\lambda(p)dm(p) + \left(A^0(\overline{p}) - \lambda c^q\right) m(\overline{p}). \end{aligned} \tag{50}$$

Now consider specifically the Lagrange multiplier $\lambda = \check{\lambda}$ from Proposition 3. Fixing any $m(\overline{p})$ $(0 \leq m(\overline{p}) \leq 1)$, $W^{\check{\lambda}}$ is maximized if $m$ puts all of the mass $m(\overline{p})$ on a point $\check{p}$ where $A^{\check{\lambda}}$ is minimized, that is,

$$m(p) = \begin{cases} 0 & \text{if } p < \check{p}, \\ m(\overline{p}) & \text{if } p \geq \check{p}. \end{cases}$$

Given such an $m$, the value of the Lagrangian can be written as

$$\begin{aligned} W^{\check{\lambda}} &= \left(-\min_p A^{\check{\lambda}}(p) + A^0(\overline{p}) - \check{\lambda} c^q\right) m(\overline{p}) \\ &= \alpha^{\check{\lambda}} m(\overline{p}) \\ &= 0, \end{aligned}$$

because $\alpha^{\check{\lambda}} = 0$ according to the assumption in Proposition 3.

In particular, $m^*$ as described in Proposition 2 maximizes $W^{\check{\lambda}}$. Thus, the first of the two Lagrangian conditions is satisfied.

It remains to verify the second condition, that the constraint (32) is satisfied with equality.

Suppose that $\check{p} \leq p^*$. Then $m^*(\overline{p}) = \check{m} = 1$ according to the formula given for $\check{m}$ in Proposition 2. Thus, (32) is satisfied with equality because

$$\begin{aligned} & (v(\overline{p}) + c^q)m^*(\overline{p}) - (b - c^q)\int_{p^*}^{\overline{p}} m^*(p')dp' \\ &= (v(\overline{p}) + c^q)\check{m} - (b - c^q)(\overline{p} - p^*)\check{m} \\ &= c^q \check{m} \\ &= c^q, \end{aligned}$$

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where we have used the definitions of $v(\overline{p})$ and $p^*$.

Now suppose that $\check{p} > p^*$. Then at $m(\overline{p}) = 1$ the left-hand side of (32) would be strictly larger than $c^q$. Thus, there exists $\check{m} < 1$ such that, at $m(\overline{p}) = \check{m}$, (32) is satisfied with equality. It is straighforward to check that the formula for $\check{m}$ given in Proposition 2 yields the required value.

Now suppose that $\lambda^* \geq 0$.

Consider the reformulated problem from *Step 1* (case $\lambda^* \geq 0$). The following three Lagrangian conditions are sufficient for a solution (see, e.g., Luenberger (1968), Chapter 8). First, there exists a number $\lambda_2 \geq 0$ ("Lagrange multiplier") such that $m^*(\cdot)$ solves the problem

$$\max_{m(\cdot)\in\Omega} \int_{\underline{p}}^{\overline{p}} ((b-c^q)K(p)+L(p))\, m(p)dp - \lambda^* \left((v(\overline{p})+c^q)m(\overline{p})-c^q\right)$$
$$- \lambda_2 \left( (v(\overline{p})+c^q)m(\overline{p}) - (b-c^q)\int_{p^*}^{\overline{p}} m(p')dp' \right). \tag{51}$$

Second, (32) is satisfied at $m = m^*$. Third, if (32) is satisfied with strict inequality at $m = m^*$, then $\lambda_2 = 0$.

In order to show that $m^*$ satisfies these conditions, we begin by rewriting the objective of the Lagrangian problem (51):

$$\begin{aligned} &= \int_{\underline{p}}^{\overline{p}} \left((b-c^q)K(p)+L(p)+\lambda_2(b-c^q)\mathbf{1}_{p\geq p^*}\right) m(p)dp - (\lambda_2+\lambda^*)(v(\overline{p})+c^q)m(\overline{p}) + \lambda^* c^q \\ &= W^{\lambda_2+\lambda^*} + \lambda^* c^q, \end{aligned} \tag{52}$$

where the last equality is immediate from a comparison with (45). Note that the term $\lambda^* c^q$ is constant and thus can be dropped from the maximization problem.

First we consider the case $\check{\lambda} \leq \lambda^*$. Fix the Lagrange multiplier $\lambda_2 = 0$. Then,

$$\alpha^{\lambda_2+\lambda^*} \leq 0 \tag{53}$$

because $\alpha$ is a decreasing function.

Fixing any $m(\overline{p})$ $(0 \leq m(\overline{p}) \leq 1)$ and applying (50) with $\lambda = \lambda_2 + \lambda^*$, we see that the objective of the Lagrangian problem is maximized if $m$ puts all of the mass $m(\overline{p})$ on a point $\check{p}$ where $A^{\lambda_2+\lambda^*}$ is minimized, that is,

$$m(p) = \begin{cases} 0 & \text{if } p < \check{p}, \\ m(\overline{p}) & \text{if } p \geq \check{p}. \end{cases}$$

Given such an $m$, the value of the Lagrangian can be written as

$$W^{\lambda_2+\lambda^*} = \alpha^{\lambda_2+\lambda^*} m(\overline{p}) + \lambda^* c^q,$$

and, due to (53), this expression is maximized by setting $m(\overline{p}) = 0$. That is, no testing is optimal. The constraint (32) is obviously satisfied.

Now suppose that $\check{\lambda} \geq \lambda^*$. Then, we consider the Lagrange multiplier $\lambda_2 = \check{\lambda} - \lambda^*$. Using the fact that the Lagrangian can be written in the form (52), the rest of the proof is as in the case $\lambda^* \leq 0$ that was treated above.

**Step 3: optimal quarantining schedule**

As in *Step 1* and in *Step 2*, we distinguish two cases depending on the sign of $\lambda^*$. Suppose first that $\lambda^* \leq 0$.

Consider first the case $\check{p} \leq p^*$. Then $\check{m} = 1$. Using (31),

$$U(\underline{p}, \underline{p}) = -(b - c^q) \int_{\check{p}}^{p^*} \check{m} dp' = -(b - c^q)(p^* - \check{p}) = v(\check{p}).$$

Thus, for all $p < \check{p}$, (24) with $m = m^*$ implies that

$$q^*(p) = \frac{1}{c^q} \left(-U(\underline{p}, \underline{p})\right) = \frac{-v(\check{p})}{c^q},$$

as was to be shown.

Now consider the case $\check{p} > p^*$. Then $\check{m} < 1$. Using (31),

$$U(\underline{p}, \underline{p}) = 0.$$

Thus, for all $p < \check{p}$, (24) with $m = m^*$ implies that $q^*(p) = 0$, as was to be shown.

For all $p \geq \check{p}$, (24) with $m = m^*$ implies that

$$\begin{aligned}
(1 - \check{m}) q^*(p) &= \frac{1}{c^q} \left( v(p)\check{m} - (b - c^q) \int_{\check{p}}^{p} \check{m} dp' - 0 \right) \\
&= \frac{1}{c^q} \left( v(p) - (b - c^q)(p - \check{p}) \right) \check{m} \\
&= \frac{1}{c^q} v(\check{p}) \check{m}.
\end{aligned}$$

Dividing both sides by $1 - \check{m}$ yields the formula

$$q^*(p) = v(\check{p}) \frac{\check{m}}{(1 - \check{m}) c^q} \quad \text{for all } p \geq \check{p}.$$

Plugging into the right-hand side the formula (14), we obtain the desired conclusion $q^*(p) = 1$.

Now suppose that $\lambda^* \geq 0$.

Consider first the case that testing nobody is optimal, $m(p) = 0$ for all $p$. Then (40) implies

$$U(\underline{p}, \underline{p}) = -c^q.$$

Thus, (24) implies that $q(p) = 1$ for all $p$, that is, everybody will be quarantined, as was to be shown.

Now consider the remaining possibility for the optimum, that is, the case with a marginally tested type $\check{p}$.

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Using (40),

$$\begin{aligned} U(\underline{p},\underline{p}) &= (v(\overline{p})+c^q)\check{m}-(b-c^q)(\overline{p}-\check{p})\check{m}-c^q \\ &= (v(\overline{p})+c^q)\check{m}-(v(\overline{p})-v(\check{p}))\check{m}-c^q \\ &= (v(\check{p})+c^q)\check{m}-c^q \end{aligned}$$

Thus, for all $p<\check{p}$, (24) with $m=m^*$ implies that

$$\begin{aligned} q^*(p) &= \frac{1}{c^q}\left(-U(\underline{p},\underline{p})\right)=\frac{-v(\check{p})}{c^q} \\ &= -\frac{v(\check{p})+c^q}{c^q}\check{m}+1. \end{aligned} \tag{54}$$

In particular, if $\check{p}\le p^*$ so that $\check{m}=1$, then

$$q^*(p)=-\frac{v(\check{p})}{c^q},$$

as was to be shown.

Finally, suppose that $\check{p}>p^*$. Then (14) implies that

$$\check{m} = \frac{c^q}{c^q+v(\check{p})}.$$

Plugging this into the formula (54) yields that, for all $p<\check{p}$,

$$q^*(p)=-\frac{v(\check{p})+c^q}{c^q}\check{m}+1=0,$$

as was to be shown.

For all $p\ge\check{p}$, (24) with $m=m^*$ implies that

$$\begin{aligned} (1-\check{m})q^*(p) &= \frac{1}{c^q}\left(v(p)\check{m}-(b-c^q)\int_{\check{p}}^{p}\check{m}dp'-((v(\check{p})+c^q)\check{m}-c^q)\right) \\ &= \frac{1}{c^q}\left(-(c^q\check{m}-c^q)\right) \\ &= 1-\check{m}. \end{aligned}$$

Dividing both sides by $1-\check{m}$ yields that

$$q^*(p) = 1,$$

as was to be shown. This completes the proof of Proposition 2 and Proposition 3.

## 5 Conclusion

The timing of individuals when deciding to get tested for an infectious disease can be crucial. Getting tested at an early stage when the symptoms are still ambiguous can be very helpful towards curbing the spread of the disease. We emphasize the government's role in providing such incentives via putting a testing-and-social-distancing schedule in place that takes the individuals' private health signals into account.

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# 6 Appendix

*Proof of Lemma 1.* Because $A^\lambda(p)$ is strictly increasing in $\lambda$ if $p > p^*$ and is independent of $\lambda$ if $p \leq p^*$, the expression $\min_p A^\lambda(p)$ is weakly increasing in $\lambda$, showing that $\alpha^\lambda$ is weakly decreasing in $\lambda$.

To show that $\alpha \mapsto \alpha^\lambda$ is Lipschitz continuous, it remains to verify that there exists a number $\overline{L} > 0$ such that, for all $\lambda_2 > \lambda_1$,

$$\alpha^{\lambda_2} - \alpha^{\lambda_1} \quad \geq \quad -\overline{L}(\lambda_2 - \lambda_1). \tag{55}$$

To see this, let $p_1$ denote a minimizer of $A^{\lambda_1}$. Then $\min_p A^{\lambda_2}(p) \leq A^{\lambda_2}(p_1)$, implying

$$\alpha^{\lambda_2} - \alpha^{\lambda_1} \geq -A^{\lambda_2}(p_1) + A^{\lambda_1}(p_1) - (\lambda_2 - \lambda_1)c^q = -\mathbf{1}_{p_1 > p^*} \cdot v(p_1)(\lambda_2 - \lambda_1) - c^q(\lambda_2 - \lambda_1),$$

so that Lipschitz continuity is satisfied with $\overline{L} = v(\overline{p}) + c^q$.

By Lipschitz continuity, the derivative $d\alpha^\lambda/d\lambda$ exists almost everywhere. Using the envelope theorem (Milgrom and Segal (2002)), and letting $p^\lambda$ denote a minimizer of $A^\lambda$,

$$\frac{d\alpha^\lambda}{d\lambda} = -\frac{d}{d\lambda} \min_p A^\lambda - c^q = -\mathbf{1}_{p^\lambda > p^*} \cdot v(p^\lambda) - c^q,$$

from which the inequalities stated in the lemma are immediate.

Note that $\alpha^0 \geq 0$ from (17).

If we choose $\lambda$ larger than $-\frac{1}{b-c^q} \min_{p>p^*} dB/dp$, then $A^\lambda$ is strictly increasing on the interval $(p^*, \overline{p}]$, showing that any minimizer of $A^\lambda$ belongs to the interval $[\underline{p}, p^*]$. For all $p$ in this interval, we have $A^\lambda(p) = B(p)$. Thus, for all sufficiently large $\lambda$,

$$\alpha^\lambda \quad = \quad -\min_{p \leq p^*} B(p) + A^0(\overline{p}) - \lambda c^q,$$

showing that $\alpha^\lambda < 0$ if $\lambda$ is sufficiently large. □

*Proof of Proposition 4.* Suppose that $\lambda^* \geq 0$ and $\alpha^{\lambda^*} \leq 0$. By Lemma 1, there exists $\check{\lambda} \leq \lambda^*$ such that $\alpha^{\check{\lambda}} = 0$. Thus, Proposition 3 implies that no-testing-always-quarantining solves the government's problem.

Now suppose that $\lambda^* < 0$, or $\lambda^* \geq 0$ and $\alpha^{\lambda^*} > 0$. By Lemma 1, there exists $\check{\lambda} \geq \max\{0, \lambda^*\}$ such that $\alpha^{\check{\lambda}} = 0$. Thus, Proposition 3 implies that the government's problem has a solution with a threshold $\check{p}$. Choose $\check{p}$ minimal if multiple solutions exist.

Note that, for all $\lambda \geq 0$ and all $p \leq p^*$, $A^\lambda(p) = B(p)$. Thus,

$$\min_{p \leq p^*} A^\lambda(p) = \underline{B}.$$

Consider first the case $\underline{B} \leq \underline{A}^{\overline{\lambda}}$. Thus,

$$\underline{B} = \min_p A^{\overline{\lambda}}(p) \leq A^{\overline{\lambda}}(\overline{p}).$$

This implies $\bar{l} \geq 0$ because otherwise we would have $\overline{\lambda} = 0$, implying $\underline{B} \leq A^0(\overline{p})$ by the inequality above, implying $\bar{l} \geq 0$ by the definition of $\bar{l}$.

Thus, $\overline{\lambda} = \bar{l}$.

Suppose that $\check{\lambda} < \overline{\lambda}$. Then $\underline{A}^{\check{\lambda}} \leq \underline{A}^{\overline{\lambda}}$, implying

$$\alpha^{\check{\lambda}} = -\min\{\underline{A}^{\check{\lambda}}, \underline{B}\} + A^0(\overline{p}) - \check{\lambda} c^q > -\min\{\underline{A}^{\overline{\lambda}}, \underline{B}\} + A^0(\overline{p}) - \overline{\lambda} c^q = -\underline{B} + A^0(\overline{p}) - \bar{l} c^q = 0,$$

contradicting the definition in Proposition 3.

Thus, $\check{\lambda} \geq \overline{\lambda}$. In the case $\underline{B} < \underline{A}^{\overline{\lambda}}$, we cannot have a solution with $\check{p} > p^*$ because this would imply

$$A^{\check{\lambda}}(\check{p}) \geq A^{\overline{\lambda}}(\check{p}) \geq \underline{A}^{\overline{\lambda}} > \underline{B},$$

contradicting the fact that $\check{p}$ minimizes $A^{\check{\lambda}}$ on the interval $[\underline{p}, \overline{p}]$.

Similarly, in the case $\underline{B} = \underline{A}^{\overline{\lambda}}$ and $\check{\lambda} > \overline{\lambda}$, we cannot have a solution with $\check{p} > p^*$ because this would imply

$$A^{\check{\lambda}}(\check{p}) > A^{\overline{\lambda}}(\check{p}) \geq \underline{A}^{\overline{\lambda}} = \underline{B},$$

again contradicting the fact that $\check{p}$ minimizes $A^{\check{\lambda}}$ on the interval $[\underline{p}, \overline{p}]$.

In the case $\underline{B} = \underline{A}^{\overline{\lambda}}$ and $\check{\lambda} = \overline{\lambda}$, the function $A^{\check{\lambda}}$ has a minimizer that is $\leq p^*$, showing that $\check{p} \leq p^*$, as claimed.

Now consider the case $\underline{B} > \underline{A}^{\overline{\lambda}}$. This implies

$$\min\{\underline{A}^{\overline{\lambda}}, \underline{B}\} < \underline{B}.$$

Suppose first that $\bar{l} \geq 0$. Then $\overline{\lambda} = \bar{l}$, implying

$$\alpha^{\overline{\lambda}} = -\min\{\underline{A}^{\overline{\lambda}}, \underline{B}\} + A^0(\overline{p}) - \overline{\lambda} c^q > -\underline{B} + A^0(\overline{p}) - \bar{l} c^q = 0,$$

Thus, $\check{\lambda} > \overline{\lambda}$ because $\alpha^{\lambda}$ is decreasing.

Suppose that $\check{p} \leq p^*$. This would imply $\underline{B} \leq \underline{A}^{\check{\lambda}}$, thus

$$\alpha^{\check{\lambda}} = -\underline{B} + A^0(\overline{p}) - \check{\lambda} c^q < -\underline{B} + A^0(\overline{p}) - \bar{l} c^q = 0,$$

contradicting the definition of $\check{\lambda}$.

Finally, consider the case $\bar{l} < 0$, that is, $A^0(\overline{p}) - \underline{B} < 0$. Suppose that $\check{p} \leq p^*$. This would imply $\underline{B} \leq \underline{A}^{\check{\lambda}}$, thus

$$\alpha^{\check{\lambda}} = -\underline{B} + A^0(\overline{p}) - \check{\lambda} c^q \leq -\underline{B} + A^0(\overline{p}) < 0,$$

contradicting the definition of $\check{\lambda}$. □

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*Proof of Corollary 2.* By Proposition 4, it is sufficient to show that $\lambda^* \geq 0$ and $\alpha^{\lambda^*} \leq 0$.

In the following, we view $\lambda^*$, $B$, and $\alpha^{\lambda^*}$ as functions of $w^1$ and $c^{gq}$. Accordingly, we use the notation $\lambda^* = \lambda^{w^1,c^{gq}}$, $B = B^{w^1,c^{gq}}$, and $\alpha^{\lambda^*} = \alpha^{w^1,c^{gq}}$.

Note that all these quantities are continuous in $w^1$ and $c^{gq}$, where $B$ is endowed with the max-norm for continuous functions on $[\underline{p}, \overline{p}]$, and the continuity of $(w^1, c^{gq}) \mapsto \alpha^{w^1,c^{gq}}$ follows from Berge's maximum theorem.

Thus, it is sufficient to show that $\lambda^{0,0} > 0$ and $\alpha^{0,0} < 0$.

By definition of $\lambda^*$,

$$\lambda^{0,0} \;=\; \frac{b^q}{c^q} E[p'] \;>\; 0.$$

Note that, for all $p$,

$$B^{0,0}(p) \;=\; \left(-c^{gt}\right) F(p) + \left(b^q + \frac{b^q}{c^q} v(p)\right) E[p'|p' \leq p] F(p).$$

Using the same arguments as in the heuristics provided below the statement of Corollary 2 (cf. (20)),

$$\alpha^{0,0} \;=\; -\min_p (B^{0,0}(p) + c^{gt}). \tag{56}$$

Fix $\epsilon > 0$ such that

$$\epsilon \;<\; \max\left\{c^{gt}(1 - F(p^*)), b^q E[p'|p' \leq p^*] F(p^*)\right\}.$$

Using the definition of $B^{0,0}$ and (21),

$$B^{0,0}(p) + c^{gt} \;\geq\; c^{gt}(1 - F(p)) \quad \text{for all } p \in [\underline{p}, \overline{p}].$$

Thus, if $p \leq p^*$, then

$$B^{0,0}(p) + c^{gt} \geq c^{gt}(1 - F(p^*)) > \epsilon.$$

If $p \geq p^*$, then

$$B^{0,0}(p) + c^{gt} \geq b^q E[p'|p' \leq p^*] F(p^*) > \epsilon.$$

Thus, (56) implies that $\alpha^{0,0} \leq -\epsilon < 0$, as was to be shown. □

*Proof of Corollary 3.* We indicate the dependence of $A^\lambda$ on $c^{gt}$ by using the notation $A^\lambda_{c^{gt}}$. Similarly, we will use the notation $\alpha^\lambda_{c^{gt}}$.

For any $\lambda \geq 0$ and any $c^{gt} > 0$, let $p^\lambda_{c^{gt}}$ denote the smallest minimizer of $A^\lambda_{c^{gt}}(p)$; the proof will be identical if we select the largest minimizer for all $\lambda$ and all $c^{gt}$. Recalling the definition (16), the envelope theorem (Milgrom and Segal (2002)) yields that the function $c^{gt} \mapsto \min_p A^\lambda_{c^{gt}}(p)$ is Lipschitz continuous and its derivative is, for Lebesgue-almost every $c^{gt}$, given by

$$\frac{d}{dc^{gt}} \min_p A^\lambda_{c^{gt}}(p) = \frac{\partial A^\lambda_{c^{gt}}}{\partial c^{gt}}(p^\lambda_{c^{gt}}) = -F(p^\lambda_{c^{gt}}).$$

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Similarly,

$$\frac{\partial}{\partial c^{gt}} A^{0}_{c^{gt}}(\overline{p}) = -1.$$

Thus, using (17),

$$\frac{\partial}{\partial c^{gt}} \alpha^{\lambda}_{c^{gt}} = F(p^{\lambda}_{c^{gt}}) - 1. \tag{57}$$

For any $c^{gt}$, let $\check{\lambda}(c^{gt})$ denote the unique point $\lambda$ where $\alpha^{\lambda}_{c^{gt}} = 0$ (cf. Lemma 1).

By (57), $\partial\alpha^{\lambda}_{c^{gt}}/\partial c^{gt} \leq 0$. Together with the fact that $\alpha^{\lambda}_{c^{gt}}$ is strictly decreasing in $\lambda$ (cf. Lemma 1), this implies that the function $c^{gt} \mapsto \check{\lambda}(c^{gt})$ is weakly decreasing. Next we show that this function is Lipschitz continuous, implying that its derivative exists almost everywhere.

Consider any two cost levels $c^{gt}_1 < c^{gt}_2$. Then

$$\begin{aligned}
0 &= \alpha^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_2} - \alpha^{\check{\lambda}(c^{gt}_1)}_{c^{gt}_1} \\
&= \alpha^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_2} - \alpha^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_1} - \left(\alpha^{\check{\lambda}(c^{gt}_1)}_{c^{gt}_1} - \alpha^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_1}\right) \\
&= \int_{c^{gt}_1}^{c^{gt}_2} \frac{\partial}{\partial c^{gt}} \alpha^{\check{\lambda}(c^{gt}_2)}_{c^{gt}} dc^{gt} - \int_{\check{\lambda}(c^{gt}_2)}^{\check{\lambda}(c^{gt}_1)} \frac{\partial \alpha^{\lambda}_{c^{gt}_1}}{\partial \lambda} d\lambda.
\end{aligned} \tag{58}$$

Thus, using (57) and the estimate $-d\alpha^{\lambda}/d\lambda \geq c^q$ from Lemma 1,

$$0 \;\geq\; (-1)(c^{gt}_2 - c^{gt}_1) + \left(\check{\lambda}(c^{gt}_1) - \check{\lambda}(c^{gt}_2)\right) c^q,$$

implying that

$$\check{\lambda}(c^{gt}_1) - \check{\lambda}(c^{gt}_2) \;\leq\; \frac{1}{c^q}(c^{gt}_2 - c^{gt}_1).$$

This completes the proof that the function $c^{gt} \mapsto \check{\lambda}(c^{gt})$ is Lipschitz continuous. Because the function is also weakly decreasing,

$$\check{\lambda}'(c^{gt}) \;\leq\; 0 \quad \text{for Lebesgue-almost every } c^{gt}.$$

Using (16), for all $p$,

$$\frac{d}{dc^{gt}} A^{\check{\lambda}(c^{gt})}_{c^{gt}}(p) \;=\; -F(p) + \mathbf{1}_{p>p^*} v(p) \check{\lambda}'(c^{gt}).$$

Thus, for all $p_1$, $p_2$ with $p_2 > p_1$, and all $c^{gt}_1$, $c^{gt}_2$ with $c^{gt}_2 > c^{gt}_1$,

$$\begin{aligned}
&A^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_2}(p_2) - A^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_2}(p_1) - \left(A^{\check{\lambda}(c^{gt}_1)}_{c^{gt}_1}(p_2) - A^{\check{\lambda}(c^{gt}_1)}_{c^{gt}_1}(p_1)\right) \\
&= A^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_2}(p_2) - A^{\check{\lambda}(c^{gt}_1)}_{c^{gt}_1}(p_2) - \left(A^{\check{\lambda}(c^{gt}_2)}_{c^{gt}_2}(p_1) - A^{\check{\lambda}(c^{gt}_1)}_{c^{gt}_1}(p_1)\right) \\
&= -\underbrace{(F(p_2) - F(p_1))}_{>0}\underbrace{(c^{gt}_2 - c^{gt}_1)}_{>0} + \underbrace{(\mathbf{1}_{p_2>p^*} v(p_2) - \mathbf{1}_{p_1>p^*} v(p_1))}_{\geq 0}\underbrace{\left(\check{\lambda}(c^{gt}_2) - \check{\lambda}(c^{gt}_1)\right)}_{\leq 0} \\
&< 0.
\end{aligned} \tag{59}$$

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Recall that

$$p_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})} \quad \in \quad \arg\min_p A_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}(p)$$

and

$$p_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})} \quad \in \quad \arg\min_p A_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})}(p).$$

Thus, for all $p < p_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}$,

$$A_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}(p_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}) - A_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}(p) \quad \leq \quad 0.$$

Applying (59) with $p_2 = p_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}$ and $p_1 = p$, we conclude that

$$A_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})}(p_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}) - A_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})}(p) \quad < \quad 0.$$

Thus,

$$p \quad \notin \quad \arg\min_p A_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})}(p),$$

implying that[17]

$$p_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})} \quad \geq \quad p_{c_1^{gt}}^{\check{\lambda}(c_1^{gt})}.$$

Thus, the marginal-type function $c^{gt} \mapsto p_{c^{gt}}^{\check{\lambda}(c^{gt})}$ is weakly increasing. An analogous argument shows that, for all $\lambda \geq 0$, the marginal-type function $c^{gt} \mapsto p_{c^{gt}}^{\lambda}$ is weakly increasing, implying that $p_{c^{gt}}^{\check{\lambda}(c_2^{gt})} \leq p_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})}$ for all $c^{gt} \leq c_2^{gt}$.

Thus, for any two cost levels $c_1^{gt} < c_2^{gt}$, (57) implies that

$$\begin{aligned}
\int_{c_1^{gt}}^{c_2^{gt}} \frac{\partial}{\partial c^{gt}} \alpha_{c^{gt}}^{\check{\lambda}(c_2^{gt})} dc^{gt} \quad &= \quad -\int_{c_1^{gt}}^{c_2^{gt}} \left(1 - F\left(p_{c^{gt}}^{\check{\lambda}(c_2^{gt})}\right)\right) dc^{gt} \\
&\leq \quad -(c_2^{gt} - c_1^{gt}) \left(1 - F\left(p_{c_2^{gt}}^{\check{\lambda}(c_2^{gt})}\right)\right).
\end{aligned}$$

On the other hand, the estimate $-d\alpha^{\lambda}/d\lambda \leq c^q + v(\overline{p})$ from Lemma 1 implies that

$$-\int_{\check{\lambda}(c_2^{gt})}^{\check{\lambda}(c_1^{gt})} \frac{\partial \alpha_{c_1^{gt}}^{\lambda}}{\partial \lambda} d\lambda \quad \leq \quad \left(\check{\lambda}(c_1^{gt}) - \check{\lambda}(c_2^{gt})\right)(c^q + v(\overline{p})).$$

[17]For a general background of this type of monotone-comparative-statics argument, see Milgrom and Shannon (1994)).

In summary, (58) implies that

$$0 \;\leq\; -(c_2^{gt} - c_1^{gt}) \left(1 - F\left(p_{c_2^{gt}}^{\check\lambda(c_2^{gt})}\right)\right) + \left(\check\lambda(c_1^{gt}) - \check\lambda(c_2^{gt})\right)(c^q + v(\overline{p})).$$

Rearranging this yields the inequality

$$\frac{\check\lambda(c_1^{gt}) - \check\lambda(c_2^{gt})}{c_2^{gt} - c_1^{gt}} \;\geq\; \frac{1}{c^q + v(\overline{p})}\left(1 - F\left(p_{c_2^{gt}}^{\check\lambda(c_2^{gt})}\right)\right).$$

Taking the limit $c_1^{gt} \to c_2^{gt}$ yields that

$$-\check\lambda'(c_2^{gt}) \;\geq\; \frac{1}{c^q + v(\overline{p})}\left(1 - F\left(p_{c_2^{gt}}^{\check\lambda(c_2^{gt})}\right)\right). \tag{60}$$

This implies

$$\lim_{c^{gt}\to\infty} p_{c^{gt}}^{\check\lambda(c^{gt})} \;=\; \overline{p}$$

because otherwise the derivative (60) is bounded away from zero for all $c^{gt}$, contradicting the fact that $\check\lambda(c^{gt}) \geq 0$.

Next, we show that

$$\lim_{c^{gt}\to\infty} \check\lambda(c^{gt}) \;=\; 0. \tag{61}$$

Otherwise there exists a sequence $(c_n^{gt})_{n=1,2,\ldots}$ with $c_n^{gt} \to \infty$ and a number $\epsilon > 0$ such that $\check\lambda(c_n^{gt}) > \epsilon$ for all $n$. Then (17) implies that

$$\begin{aligned}
&\limsup_n \alpha_{c_n^{gt}}^{\check\lambda(c_n^{gt})}\\
\leq\;& \limsup_n \left(-A_{c_n^{gt}}^{\check\lambda(c_n^{gt})}(p_{c_n^{gt}}^{\check\lambda(c_n^{gt})}) + A_{c_n^{gt}}^0(\overline{p})\right) - \liminf_n \check\lambda(c_n^{gt})c^q\\
\leq\;& \limsup_n \left(-A_{c_n^{gt}}^{\check\lambda(c_n^{gt})}(\overline{p}) + A_{c_n^{gt}}^0(\overline{p})\right) + \limsup_n \left(A_{c_n^{gt}}^{\check\lambda(c_n^{gt})}(\overline{p}) - A_{c_n^{gt}}^{\check\lambda(c_n^{gt})}(p_{c_n^{gt}}^{\check\lambda(c_n^{gt})})\right) - \liminf_n \check\lambda(c_n^{gt})c^q\\
\leq\;& -v(\overline{p})\epsilon + 0 - \epsilon c^q < 0,
\end{aligned}$$

contradicting the optimality condition $\alpha_{c_n^{gt}}^{\check\lambda(c_n^{gt})} = 0$ from Proposition 3.

The condition $w^1 \geq \frac{b^q E_{p'\sim F}[p'] - c^{gq}}{c^q}$ is equivalent to the condition $\lambda^* \leq 0$.

The opposite condition $w^1 < \frac{b^q E_{p'\sim F}[p'] - c^{gq}}{c^q}$ means that $\lambda^* > 0$. From (61), there exists $\overline{c}^{gt}$ be such that $\check\lambda(\overline{c}^{gt}) = \lambda^*$.

Setting $\check p = p_{c^{gt}}^{\check\lambda(c^{gt})}$, the desired claims hold by Proposition 3. □

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# What comes next: Scenarios for the recovery[1]

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*The Covid crisis prompted an unprecedented global economic contraction. Although the worst is likely behind us, the recovery is likely to be uneven, with economic activity in many customer-facing service industries set to remain constrained for some time. I use a quantitative multi-industry model to estimate the economic forces that explain the decline in economic activity in the United States, the Euro Area, Japan and China in the first half of 2020. I then use the model to project the trajectory of the economic recovery. I find that the US, EA and Japan will each face a `98% economy' if half of the constraints faced by customer-facing service industries in the first half of 2020 persist. The economic recovery in China is projected to occur more quickly.*

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## 1 Introduction

The Covid crisis has triggered unprecedented decline in global economic activity. In many Advanced Economies (AEs), output contracted by more than 10% in the first half of 2020. Some Emerging Market Economies (EMEs) saw even sharper downturns. In China, whose economy had experienced sustained growth for almost three decades, year-on-year GDP growth turned negative for the first time since the early 1990s.

The economic contraction was felt unevenly across industries. Services that involve personal interactions between customers and workers were hit particularly hard. In the United States (US), consumption of recreation services declined by 49% in 2020Q2, and consumption of transport services by 34%. In contrast, consumption of durable goods, which typically contracts sharply during recessions, fell by only 0.3%. Consumption of recreational goods actually increased. Similar patterns were observed in other economies.

While the trough in economic activity seems to have passed, the recovery looks set to be slow and uneven. Some industries have recovered quickly after the easing of explicit lockdown measures. But many firms, particularly in customer-facing service industries, face ongoing constraints. These include regulatory restrictions on how firms operate as well as voluntary changes in behaviour as customers seek to avoid activities that put them at greater risk of contracting the virus. Some of these constraints are likely to persist until a vaccine or effective treatment is available.

The unevenness of the recovery has led to speculation that many countries could face a '90% economy' in the years ahead.[1] According to this view, depressed conditions in customer-facing service industries will create an ongoing 'hole' in aggregate demand. Firms in these industries will demand fewer inputs from their suppliers, lowering output throughout their supply chains. As firms directly affected by the pandemic cut back on production, the resulting loss of income for workers and shareholders will lower aggregate demand more broadly, deepening the slump further.

At the same time, there are several reasons to think that economies could recover more strongly than the '90% economy' view might suggest. A large part of the decline in economic activity in the first half of the year was due to aggregate forces such as broad-based lockdowns, heightened precautionary saving by consumers and dislocations in financial markets. In part, these responses reflected high levels of uncertainty about the nature of the virus as it spread around the world in the first few months of the year (Baker et al. (2020)). Much of this uncertainty has since been resolved in recent months as the medical community's understanding of the virus and ability to treat its symptoms, has increased. And in most regions, blanket lockdowns have given way to more targeted measures. In the meantime, in many economies monetary and fiscal policymakers have provided considerable stimulus to support aggregate demand and introduced measures to improve the functioning of financial markets. These policies should contribute to an improvement in economic conditions.

At an aggregate level, some of the loss of custom experienced by firms particularly exposed to the virus could also be made up for by increased demand for other goods and services. This could be due to shifts in consumer preferences across industries - eg if less demand for restaurant meals leads to more demand for

[1]See, for example: The Economist (2020a)

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food that can be consumed at home - or changes within industries - eg if less foot traffic at retail outlets is replaced by purchases made online. Some of these shifts could merely represent an acceleration of existing trends and some may even be productivity-enhancing. To be sure, the shifts in the composition of demand that the virus has prompted will involve severe disruptions for individual firms and workers. Policy may have an important role to play in helping firms and workers to cope with those disruptions. But it is not clear that these shifts will have large negative effects at an aggregate level.

A number of factors will therefore determine 'what comes next' for global economic activity. Among the most important are the nature of the disturbances affecting individual economies; whether they represent aggregate or industry-specific disturbances and whether they reflect shifts in demand or in supply. The evolution of these disturbances will also matter greatly. And much will depend on how smoothly economies can accommodate the changes in industrial composition that these aggregate and industry-level disturbances will entail.

This paper provides quantitative estimates of these forces. To this end, I build an economic model to capture the key industry-level and aggregate transmission mechanisms that were at work during the Covid crisis and which will shape the recovery. In addition to the usual set of nominal and real rigidities typically used to account for aggregate economic fluctuations, the model features a detailed industry structure on both the demand and production side. This allows it to account for industry-specific shifts in consumer preferences and work practices, and then to project the implications of these shifts for aggregate outcomes. I calibrate the model to match the industrial structure of the US, the Euro Area (EA), Japan and China. I then use the model to estimate the aggregate- and industry-level supply and demand disturbances that explain the contraction in economic activity in the first half of 2020. Conditional on these disturbances, I construct projections for how economic activity could evolve over the coming years.

I find that the US, EA and Japan could each face a '98% economy' over the next few years. That is, even factoring in a fairly rapid economic recovery into the first half of 2021, these economies could see output stagnate persistently 2% below its pre-crisis trend. The recovery is also likely to result in a greater-than-usual degree of industry re-allocation. In particular, the output of customer-facing service industries is projected to remain between 10 and 20% below its pre-crisis trajectory for several years in these three economies.

My results indicate that aggregate economic activity in China will recover more quickly than in the other economies. Under the model's baseline scenario, output in China returns to its pre-crisis trajectory by the end of 2021. However, the recovery in China is also uneven at an industry level. Output in customer-facing service industries is projected to remain more than 5% below its pre-crisis trajectory. The relatively small weight of these industries in aggregate economic activity in China, and a more rapid recovery in other parts of the economy, explain the more positive projections for aggregate output.

The baseline projections rest on two key assumptions: first, that the economy-wide forces constraining economic activity in the first half of 2020 dissipate over the rest of the year; and second, that around half of the disturbances specific to customer-facing service industries persist until mid-2023. Under the more optimistic assumption that the constraints on customer-facing service industries loosen in the first half of 2021, the level of activity in all four economies is estimated to return to its pre-crisis trajectory by early 2022. However, under the more pessimistic assumption that customer-facing service industries face more severe constraints that persist until mid-2025, the US, EA and Japan could face a '95% economy', with activity stagnating 5 per cent below its pre-crisis trajectory.

The rest of the paper is as follows. Section 2 lays out the model the model and describes the differential effects of industry-level supply and demand disturbances. Section 3 explains the economic developments that determined the Covid crisis. Section 4 provides projections under a range of scenarios. Section 5 concludes.

## 2 Model and calibration

In this section I provide a description of the essential features of the model, and describe its calibration. As many features of the model are standard, I focus on those aspects most relevant for the modelling the Covid crisis and direct readers interested in the full set of model equations to the Online Appendix accompanying the paper.[2]

### 2.1 The Model

The model consists of a closed economy whose main actors are households, firms, the government and the central bank.

Households come in two types. The first, termed 'Ricardian' households, are able to borrow and save in financial markets. These households make consumption, work, investment and saving decisions in order to maximise their discounted lifetime utility, subject to an intertemporal budget constraint. For example, the utility function of Ricardian household $\iota$ is given by:

$$\sum_{t=0}^{\infty}\beta^t\left[e^{\xi_{c,t}}\log(C_t^r(\iota)-hC_{t-1}^r(\iota))-\frac{A_N}{1+\nu}N_t^r(\iota)^{1+\nu}\right] \tag{1}$$

where $C_t^r(\iota)$ is the total consumption of the household and $N_t^r(\iota)$ is the total labour supply of the household. The term $e^{\xi_{c,t}}$, which is common to all households, is a 'preference shifter'. Movements in this term induce changes in consumption independent of other factors such as income or interest rates.

The budget constraint of a typical Ricardian household is given by:

$$P_{C,t}C_t^r(\iota)+P_{I,t}I_t^r(\iota)+\frac{B_{t+1}^r(\iota)}{R_t}\leq B_t^r(\iota)+\sum_{j=1}^{\mathcal{F}}\left(P_{C,t}\frac{r_{j,t}^K}{\mathcal{M}_t}k_{j,t}^r(\iota)+w_{j,t}(\iota)n_{j,t}^r(\iota)\right)+T_t^r(\iota) \tag{2}$$

where $I_t^r(\iota)$ is the household's total investment in physical capital, $P_{C,t}$ and $P_{I,t}$ are the prices of the investment and consumption goods, $B_{t+1}^r(\iota)$ is a risk free nominal bond that pays one unit of the consumption good in period $t+1$, $R_t$ is the interest rate attached to that bond and $T_t^r(\iota)$ are lump sum transfers from the government to Ricardian households.[3] There are $\mathcal{F}$ industries in the economy (examples of industries include the Agriculture industry or the Manufacturing industry). The variables $k_{j,t}^r(\iota)$ and

[2] The Online Appendix is available at: https://www.bis.org/publ/work898.htm.
[3] These transfers can be either positive or negative.

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$n^r_{j,t}(\iota)$ represent total supply of capital and labour from the household to industry $j$.[4] The variables $r^k_{j,t}$ and $w_{h,t}$ are the return on capital and nominal wages paid by that industry. The variable $\mathcal{M}_t$ introduces a wedge between the return on capital paid by firms and that received by households. It is included as a reduced form device to capture the tendency for spreads between risk free interest rates and returns on risky assets to widen during times of heightened economic uncertainty.[5]

The second type of households, termed 'hand-to-mouth' households have a similar utility function to the Ricardian households. However, these households are financially constrained, meaning that each period their consumption is exactly equal to their income, which consists of wage income and transfers from the government. As such, these households also do no investment and do not own claims to the capital stock of firms. The inclusion of 'hand-to-mouth' households strengthens income effects in the model as the consumption of these individuals is highly sensitive to labour market conditions.

The aggregate consumption and investment goods in Equation 2 consist of bundles of products from individual industries. For example, the aggregate consumption bundle for Ricardian consumers is:

$$C^r_t = \left[ \sum_{j=1}^{\mathcal{F}} \omega_{cj}^{\frac{1}{\eta}} (c^r_{j,t})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{3}$$

where $c^r_{j,t}$ is the consumption of the output of industry $j$ at time $t$ for Ricardian consumers.[6] The parameter $\omega_{c,j}$ controls the weight of industry $j$ in the aggregate consumption bundle. A shift in consumer preferences from, say, eating food at restaurants (a Recreation service) towards purchasing food for consumption at home (a Retail trade service) would appear in the model as a change in $\omega_{c,j}$.[7] The parameter $\eta$ controls the degree of substitutability between the output of different industries in consumption. If $\eta$ is large, different industries' output are close substitutes. If $\eta$ is close to zero, consumers are less willing to substitute between the output of different industries.

The aggregate labour supply that appears in the household utility function also consists of a weighted sum of labour supply to individual industries:

$$N^r_t(\iota) = \left[ \sum_{j=1}^{\mathcal{F}} \omega_{nj}^{-\frac{1}{\xi}} n_{j,t}(\iota)^{\frac{\xi+1}{\xi}} \right]^{\frac{\xi}{\xi+1}} \tag{4}$$

where the term $\omega_{nj}$ captures the relative disutility that the household receives from supply labour to industry $j$ and $\xi$ controls the substitutability of work in different industries. If $\xi = \infty$ workers are indifferent between which industries they work in. For smaller values of $\xi$ workers are less willing to move between industries.

[4] The economy features a single investment good, which can be used to produce capital in any industry. However, once installed, capital is industry-specific. This limits the speed with which the economy's production structure can respond to shifts in demand or supply in an individual industry.

[5] I assume that financial intermediaries return this wedge lump sum to the Ricardian households so that it does not affect their total lifetime income.

[6] The functional form of the consumption bundle for rule-of-thumb consumers is identical to that for Ricardian consumers.

[7] Because the weights in the consumption basket must sum to one, a decrease in $\omega_{c,j}$ for one industry must be offset by an increase in the weight for at least one other industry.

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On the production side of the model, each industry consists of a large number of firms that produce differentiated varieties under conditions of monopolistic competition. Individual firms produce output using a multi-stage production process. The first stage of the process combines labour and capital according to the production function:

$$f_{j,t}(i) = \left[\omega_{f,j}^{\frac{1}{\zeta}} n_{j,t}(i)^{\frac{\zeta-1}{\zeta}} + (1-\omega_{f,j})^{\frac{1}{\zeta}} k_{j,t}(i)^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}} \tag{5}$$

where $f_{j,t}(i)$ is the output produced by combining capital and labour firm $i$ in industry $j$ and $n_{j,t}(i)$ and $k_{j,t}(i)$ are the amount of labour and capital used by the firm. The parameter $\zeta$ is the elasticity of substitution between capital and labour in the production function.

The resulting output is then combined with intermediate inputs - goods and services sourced from other industries:

$$y_{j,t}(i) = a_{j,t}\left[\omega_{y,j}^{\frac{1}{\varphi}} f_{j,t}(i)^{\frac{\varphi-1}{\varphi}} + (1-\omega_{y,j}) x_{j,t}(i)^{\frac{\varphi-1}{\varphi}}\right]^{\frac{\varphi}{\varphi-1}} \tag{6}$$

where $y_{j,t}(i)$ is the gross output of firm $i$ in in industry $j$. Because of the use of intermediate inputs, a distinction exists between the gross output of an industry and value added output. The latter is calculated by subtracting the value of intermediate inputs from gross output. The term $a_{j,t}$ is industry-specific total factor productivity in industry $j$ (which is common to all firms in that industry). $x_{j,t}(i)$ is the quantity of intermediate inputs used in industry $j$. The parameter $\varphi$ is the elasticity of substitution between intermediate inputs and the aggregate of labour and capital.[8]

Market clearing for the output of industry $j$ requires that the gross output of the industry, $y_{j,t}$ equals the sum of demand for the good as a consumption good ($c_{j,t}$), investment good ($i_{j,t}$) and public demand good ($g_{j,t}$), or as an intermediate input:

$$y_{j,t} = c_{j,t} + i_{j,t} + g_{j,t} + \sum_{k=1}^{\mathcal{F}} x_{k,j,t} \tag{7}$$

where $x_{k,j,t}$ is the quantity of the output of industry $j$ used as an intermediate input in industry $k$.

The existence of intermediate inputs creates production-side linkages between industries. For example, a decrease in output in the manufacturing industry will also lower demand for the output of industries that provide intermediate inputs to that industry. Similarly, lower productivity in the manufacturing industry will raise costs for firms in industries that use manufacturing as an input into production. The importance of these inter-industry linkages will depend on the weight of intermediate inputs in industry production functions and in the substitutability between intermediate inputs and other factors. Product differentiation means that firms are able to exert a degree of pricing power. Similarly, households are assumed to unionise, giving them a degree of monopoly power in the labour market. Both firms and unions face frictions that limit their ability to reset their prices and wages each period. These generate nominal rigidities in the

[8] The intermediate input is itself a bundle of intermediate goods from the other industries: $x_{j,t} = \left[\sum_{k=1}^{\mathcal{F}} \omega_{k,j}^{\frac{1}{\psi}} x_{k,j,t}(i)^{\frac{\psi-1}{\psi}}\right]^{\frac{\psi}{\psi-1}}$, where $\psi$ is the elasticity of substitution between different varieties of intermediate goods.

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**Table 1:** Common parameter values

| Parameter | Description | Value |
|---|---|---|
| $h$ | Degree of habits in consumption | 0.7 |
| $S''$ | Investment adjustment cost | 3 |
| $\theta_w$ | Calvo parameter for wages | 0.65 |
| $\theta_p^s$ | Calvo parameter for sticky prices | 0.7 |
| $\theta_p^f$ | Calvo parameter for semi-sticky prices | 0.5 |
| $\psi$ | Substitutability of labour and capital in production | 0.95 |
| $\psi$ | Substitutability of different intermediate products in production | 0.5 |
| $\varphi$ | Substituability of primary factors and intermediates in production | 0.6 |
| $\nu$ | Aggregate labour supply elasticity | 2 |
| $\delta$ | Capital discount rate | 0.02 |
| $\eta$ | Substitution elasticity in demand functions | 0.9 |
| $\xi$ | Substitution elasticity between industries in labour supply | 2 |
| $\omega_r$ | Share of Ricardian households | 0.75 |
| $\beta$ | Household discount rate | 0.995 |

model. Real rigidities come from the presence of habits in the household utility function and quadratic adjustment costs in investment.

The government in the model fulfils two function. First, it purchases goods and services directly from firms.[9] I assume that this source of aggregate demand follows an exogenous AR(1) process. Second, it transfers resources between Ricardian and rule-of-thumb consumers.

The model's central bank adjusts the policy interest rate in response to deviations of inflation from target. In practice, several of the central banks in the empirical exercise below have limited ability to stimulate economic activity by lowering their policy interest rates and have adopted unconventional tools such as quantitative easing and forward guidance as their primary policy instruments. The model setup implicitly assumes that these unconventional tools are an effective substitute for interest rate-based monetary policy, meaning that these central banks can be viewed as acting as though they continue to follow a conventional policy rule.[10]

### 2.2 Calibration

I calibrate the model to match features of four large economies: the US, the EA, China and Japan. For each country, I use the most recent input-output tables to pin down: the weights of capital, labour and industry-specific intermediate inputs in the industry production functions, the weights of consumption, investment and government spending in domestic demand and the weights of each industry in the consumption, investment and government spending bundles.[11]

[9] As the model abstracts from international trade, this role of government could stand in for all exogenous demand, including for exports.

[10] This is consistent with the evidence in Debortoli et al. (2019) that the response of US economic variables to macroeconomic shocks did not change during the period when the Federal Funds rate was pegged at zero between 2009Q1 and 2015Q4.

[11] I model industries at the 1-digit NAISC level.

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Most of the parameters controlling the dynamics of the model, such as the habits and investment adjustment cost parameters, or the aggregate labour supply elasticity, have been estimated in similar models many times before. I set the values for these parameters close to the mid-point of estimates from papers such as Smets and Wouters (2007) and Justiniano et al. (2013) for the US and Coenen et al. (2018) and Albonico et al. (2017) for the EA.

The assumption of sticky prices is clearly unrealistic for industries such as Agriculture or Mining, whose goods are largely homogeneous and whose prices can vary enormously from quarter to quarter. For these industries I set the Calvo parameter equal to 0.05, meaning that their prices are almost fully flexible. For the remaining sectors, I rely on information about sectoral differences in the frequency of price adjustment from Bryan and Meyer (2010) and Eusepi et al. (2011). These papers suggest that manufacturing and retail prices are more flexible than those of other sectors, particularly services industries. Consequently, I set the Calvo parameter governing the frequency of price adjustment in the manufacturing and retail industries equal to 0.5, implying an average frequency of price adjustment of two quarters. For all other industries, I set the Calvo parameter equal to 0.7, which is a standard estimate for the value of this parameter in single industry models.

I base the elasticities of substitution in the demand and production functions on available estimates in the literature. For the elasticity of substitution between the output of different industries in final expenditure, I use the value of 0.9 estimated in Herrendorf et al. (2013). For the elasticity of substitution between final goods and intermediate expenditures, I follow Baqaee and Farhi (2020) in choosing a value of 0.6. Estimates of the elasticity of substitution between intermediates suggest that the value of this parameter could be close to zero (Atalay (2017)). However, preliminary investigation revealed that extremely low values of this parameter, in conjunction with the enormous changes in industry output observed in the first half of 2020, led to a large degree of model instability. Therefore, I set this parameter equal to 0.5. This means that intermediate inputs are less substitutable than other components of the demand and production functions while ensuring that it remains possible to solve the model numerically.

For the parameter governing the elasticity of substitution between industries in labour supply, I use the estimate of 2 from Horvath (2000). Finally, I set the share of Ricardian households in each economy to 0.75, which is roughly half way between the estimates of Debortoli and Gali (2017) for the US and Albonico et al. (2017) for the EA.

## 3 Modelling the Crisis

### 3.1 Unprecedented Changes in Economic Structure

In working with rational expectations models of the type described above it is common to first linearise the model around its non-stochastic steady state and then examine the effect of small perturbations, or shocks, that drive the economy away from this steady state. This approach will be accurate so long as the perturbations are sufficiently small that the structure of the economy remains unchanged. In the case of standard business cycle fluctuations, this assumption may be justified. But it less plausible in the context of the Covid crisis, which not only led to an unprecedented decline in aggregate economic activity, but also prompted large, and likely persistent, changes in business practices and in the composition of output and demand.

To account for the these changes, I model the Covid crisis as a sequence of structural changes, following the approach described in Kulish and Pagan (2017).[12]

Specifically, I assume that that up to 2019Q4 the structure of the economy could be described by the system of equations:

$$\mathbf{A}x_t = \mathbf{C} + \mathbf{B}x_{t-1} + \mathbf{D}\mathbb{E}_t\{x_{t+1}\} + \mathbf{F}\varepsilon_t \tag{8}$$

where $x_t$ is the vector of model variables and $\varepsilon_t$ is a vector of exogenous i.i.d. shocks. The matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{D}$ and $\mathbf{F}$ are the equation coefficients consistent with the initial structure of the economy. Note that by including $\mathbf{C}$ I am explicitly accounting for the steady state of the model in the solution matrices.

If it exists and is unique, the standard rational expectations solution to Equation (8) is the VAR:

$$x_t = \mathbf{J} + \mathbf{Q}x_{t-1} + \mathbf{G}\varepsilon_t \tag{9}$$

where the reduced form matrices $\mathbf{J}$, $\mathbf{Q}$ and $\mathbf{G}$ are constant, consistent with the stable economic structure.

In solving the model for 2020Q1, I allow the structure of the economy to change, to become:

$$\bar{\mathbf{A}}x_t = \bar{\mathbf{C}} + \bar{\mathbf{B}}x_{t-1} + \bar{\mathbf{D}}\mathbb{E}_t\{x_{t+1}\} + \bar{\mathbf{F}}\varepsilon_t \tag{10}$$

where $\bar{\mathbf{A}}$, $\bar{\mathbf{B}}$, $\bar{\mathbf{C}}$, $\bar{\mathbf{D}}$ and $\bar{\mathbf{F}}$ are the equation coefficients consistent with the structure of the economy that prevailed in 2020Q1. Changes in the structure of the economy could include restrictions on business operations that affect the efficiency with which firms can operate or changes in consumer behaviour, such as the avoidance of crowded retail locations where the probability of contracting the virus is elevated. Once again, the inclusion of a constant in Equation (10) means that I allow the economy's steady state, as well as the dynamic relationship between variables, to change as a result of the Covid crisis.

The solution to Equation (10) depends upon agents' beliefs about the economic structure that will prevail in the future. For 2020Q1 I assume that agents anticipated that the change in the economic structure would be temporary and that from 2020Q2 the economy would revert to its original form.[13] This is consistent with economic forecasts at the time, which until late in the quarter pointed to a rapid recovery in output in the second half of 2020.[14] The reduced form solution for 2020Q1 therefore accounts for both the structural changes that occurred in that quarter, as well as an anticipated reversion to more normal conditions subsequently.[15]

[12] Applications of this approach to model structural changes include Kulish and Rees (2000) in the context of permanent changes in commodity prices and Gomez-Gonzalez and Rees (2018) in the context of entry to a monetary union and Jones (2020) in the context of demographic change.

[13] This does not imply that the economy would recover fully in 2020Q2, as the drop in output in 2020Q1 would take time to unwind. Instead, it assumes that the relationships between variables would have been similar to they had been prior to the Covid crisis.

[14] For example, the mean forecasts for year-on-year GDP growth in 2020 the March Consensus Economics survey were 1.4% for the US, 0.9% for the euro area and 1.0% for Japan.

[15] Specifically, the reduced form solution is: $x_t = \bar{\mathbf{J}} + \bar{\mathbf{Q}}x_{t-1} + \bar{\mathbf{G}}\varepsilon_t$, where $\bar{\mathbf{J}} = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q})^{-1}(\bar{\mathbf{C}} + \bar{\mathbf{D}}\mathbf{J})$, $\bar{\mathbf{Q}} = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q})^{-1}\bar{\mathbf{B}}$ and $\bar{\mathbf{G}} = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q})^{-1}\bar{\mathbf{F}}$.

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As it turned out, constraints on economic activity, both regulatory and induced by behavioural shifts, increased in 2020Q2 before receding somewhat in 2020Q3. Moreover, it was clear by the middle of the year that the return to economic normality would take some time. Therefore, in solving the model, I allow for subsequent structural breaks in 2020Q2 and 2020Q3. I also assume that agents in the model take the likely persistence of these changes in economic structure into account in their economic decision-making.

Specifically, assume that the structure of the economy prevailing in 2020Q3 is:

$$\tilde{\mathbf{A}}x_t = \tilde{\mathbf{C}} + \tilde{\mathbf{B}}x_{t-1} + \tilde{\mathbf{D}}\mathbb{E}_t\{x_{t+1}\} + \tilde{\mathbf{F}}\varepsilon_t \tag{11}$$

where $\tilde{\mathbf{A}}$, $\tilde{\mathbf{B}}$, $\tilde{\mathbf{C}}$, $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{F}}$ are the equation coefficients consistent with the structure of the economy that prevailed in 2020Q3. And assume that agents expect that at some future period $\mathbf{T}$ the economy will revert to the economic structure that prevailed prior to the crisis. The solution to the model between 2020Q3 and $\mathbf{T}$ is a time-varying VAR of the form:

$$x_t = \mathbf{J}_t + \mathbf{Q}_t x_{t-1} + \mathbf{G}_t\varepsilon_t \tag{12}$$

where the time-varying reduced form matrices are given by:

$$\mathbf{J}_t = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}_{t+1})^{-1}(\bar{\mathbf{C}} + \bar{\mathbf{D}}\mathbf{J}_{t+1}) \tag{13}$$

$$\mathbf{Q}_t = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}_{t+1})^{-1}\bar{\mathbf{B}} \tag{14}$$

$$\mathbf{G}_t = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}_{t+1})^{-1}\bar{\mathbf{F}} \tag{15}$$

As we know the values of $\mathbf{Q}_\mathbf{T}$ and $\mathbf{J}_\mathbf{T}$, one can solve this system of equations recursively to derive the sequence of reduced form matrices from the start of the crisis to its resolution.

### 3.2 Structural changes during the Covid crisis

I model the Covid crisis as a sequence of aggregate and industry-specific disturbances. The aggregate disturbances are:

1. A change in productivity that is common to all sectors, through a proportional shift in the means of $a_{j,t}$;
2. A change in aggregate "desired consumption", through a shift in the mean of $\xi_{c,t}$;
3. A change in the steady-state spread between risk free rates and required returns on capital, through a shift in the mean of $\mathcal{M}_t$; and
4. A change in the exogenous component of demand, which I model as a transitory shock to government spending.

The intuition for the aggregate disturbances is as follows. The change in productivity captures constraints on work practices that affected the efficiency with which firms could operate during the crisis. Examples could include restrictions on restaurant occupancy rates, shifts to remote working or changing workplace arrangements to limit personal interactions between workers. The change in desired consumption captures a general diminished appetite for consumption, which could reflect formal restrictions on mobility, consumer reluctance to expose themselves to the virus or precautionary saving. The change in the capital wedge captures changes in spreads between risk-free and risky borrowing rates, as well as the increased option value of delaying investments at a time of heightened uncertainty. The shift in the exogenous component of expenditure captures changes in government spending on goods and services, as well as net trade and any other components of GDP not explicitly modelled. Because I am working with a general equilibrium model, each of the disturbances will affect all of the other variables in the model. For example, it could turn out that the behaviour of investment is fully explained by the productivity and consumption disturbances, with no role for the return on capital wedge.

In addition to these aggregate disturbances, I allow for idiosyncratic disturbances to industries that have been particularly affected by the pandemic and face ongoing constraints. For this, I focus on industries that rely heavily on face-to-face interaction with customers, where opportunities for remote work are limited. I label these industries as 'customer-facing service industries'. The selection of industries varies slightly between economies depending on how individual statistical agencies classify industries in their input-output tables and national accounts. However, they broadly include the retail trade industry, recreation industry, transport industry, social services industry and other services industry.[16]

The industry-specific disturbances consist of:

1. A change in productivity that is idiosyncratic to each industry, that is a change in $a_{j,t}$ for individual customer-facing service industries;

2. A change in the weight of each industry in the aggregate consumption bundle, that is a change in $\omega_{c,j}$.[17]

The productivity disturbance captures the possibility that constraints on operations may bind particularly tightly on service industries (for example, restrictions on customer numbers in restaurants or retail stores). The industry-specific consumption disturbance captures the idea that the Covid crisis could have led to a substitution of customer preferences away from activities deemed to be more risky. The estimation procedure, however, does not constrain these disturbances to have a negative effect on these industries. For example, it is free to conclude that productivity in the retail sector increased, potentially due to a shift from bricks-and-mortar retailers to online purchases.

The choice of industries to include in the group of those highly affected by the pandemic involves a degree of judgement. Many manufacturing and construction jobs, for example, cannot be performed remotely. And several well-publicised virus outbreaks have occurred at manufacturing plants. One could make the case that these industries have been highly affected by the virus. At the same time, in most economies these industries did not exhibit the large and persistent declines in output seen in industries like transport and recreation. Moreover, these industries supply a relatively small share of their output directly to

[16] The recreation industry includes activities such as accommodation and restaurants, the social services industry includes activities such as education and health care, the other services industries includes activities such as dry cleaning and laundry services and the services of religious organisations.

[17] With an offsetting adjustment to the weights of other industries to ensure that the weights sum to unity.

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households. Instead, changes in demand for their output due to shifts in consumption patterns is more likely to show up as changes in the demand for intermediate inputs. This justifies their exclusion from the list of highly affected industries.

The inclusion of retail trade in the list of affected industries may also be controversial. The Covid crisis has clearly had large effects *within* the retail sector. Many bricks-and-morter retailers struggled. But others, particularly those with a large online presence as well as food retailers, saw an increase in demand. The net effects of these changes for demand and productivity in the retail sector is unclear. This, however, makes it important to include this sector in the list of affected industries as its experiences and outlook could conceivably differ materially from that of the aggregate economy.

### 3.3 Changes in sectoral supply and demand

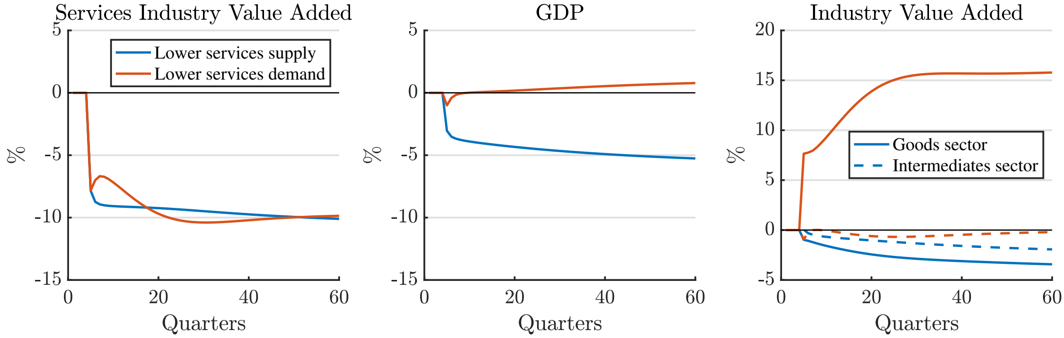
Before turning to the application to the Covid recession, it will be useful to first consider the effects of industry-level supply and demand disturbances in a simpler case.

For this exercise, I work with a stylised version of the model with three sectors: a services sector, a goods sector and an intermediates sector. The services and goods sectors produce final output for consumption and investment. The output of the intermediates sector is used in the production of services and goods.

I then consider two disturbances. The first, a supply disturbance, permanently lowers productivity in the services sector. The second, a demand disturbance, permanently shifts consumer preferences away from services consumption and towards goods consumption. I scale the changes in supply and demand so that value-added in the services sector declines by 10%.

Figure 1 shows the results of these exercises for value-added output in the services sector, aggregate GDP, and value-added output in the goods and intermediates sectors.

**Figure 1: Sectoral demand and supply disturbances**




Source: Author's calculations.

From the perspective of the services sector, the two scenarios look much the same - output declines by 10%.[18] For aggregate economic activity, however, the scenarios differ greatly. A decline in services sector

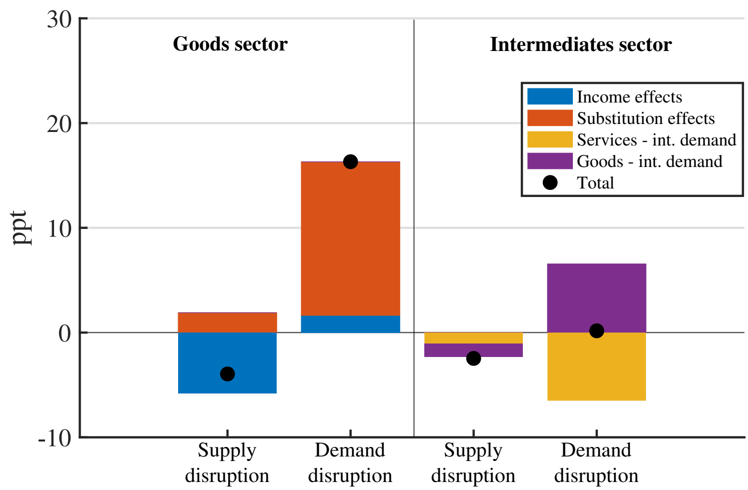
[18]There scenarios have different implications for labour and capital demand, as well as for price changes in the services

productivity leaves the economy permanently poorer. The decline in productivity lowers real incomes, which reduces aggregate demand. At the same time, the relative price of services rises, which leads households to substitute away from services towards goods. Both forces contribute to lower services output. Goods output also declines because the relatively low degree of substitutability between goods and services in the consumption bundle means that the income effect of lower aggregate economic activity overwhelms the substitution effect of lower relative goods prices. The left panel of Figure 2 shows the relative contribution of these *income* and *substitution* effects to the total change in goods output. Output in the intermediates sector also declines because, with lower output in the services and goods sector, there is less demand for intermediate inputs from both the goods and services industries.

In contrast, the preference shift shows up largely as a re-orientation of final demand from the services sector to the goods sector. As productivity is unchanged there is a relatively small income effect in this case. There is, however, a large substitution effect, which ensures that output in the goods sector unambiguously increases. In contrast, total output in the intermediates sector is largely unaffected. However, the direction of intermediates output changes, with a larger share of output being produced for the expanding goods sector and less for the declining services sector. In aggregate, GDP is also largely unaffected as the decline in services output is roughly offset by the increase in goods production.

The example described in this section is highly stylised. Real economies feature a far richer and more complex mix of intersectoral linkages. Nevertheless, the conclusion that the evolution of aggregate economic activity in response to industry-specific disruptions depends on the nature of those disruptions is a general one.

**Figure 2: Contributions to changes in industry value-added**




Note: "Services - int. demand" refers to demand for intermediate inputs by the services industry; "Goods - int. demand" refers to demand for intermediate inputs by the goods industry.

Source: Author's calculations.

sector, however.

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### 3.4 What disturbances explain the Covid crisis?

I now turn to the application to the Covid crisis.

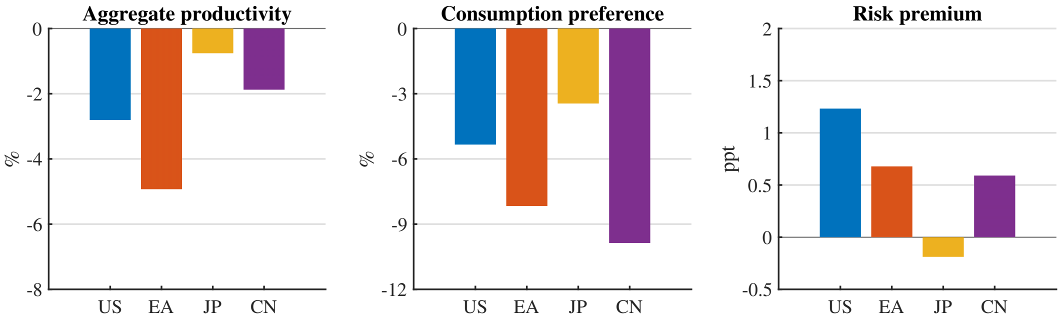
For each economy, I use a numerical procedure to recover the structural changes that the model requires to explain the economic developments that occurred during the first half of 2020.[19] Because I allow for four aggregate disturbances, I target four aggregate series: GDP growth, consumption growth, investment growth and the growth rate of the consumption deflator.[20] For the customer-facing services industries I target industry-level consumption growth and inflation.[21]

For each series, I first estimate a naive autoregressive model using data from 2000Q1 to 2019Q4. I use these models to forecast the growth rate of each series in 2020Q1 and 2020Q2. I treat these forecasts as the counterfactural of how economic variables would have evolved in the absence of the Covid crisis. The estimation algorithm then chooses the sequence of structural changes that allows the structural model to match the deviations between actual outcomes and the autoregressive forecasts. This approach assumes that all of the deviations between actual and forecast outcomes can be attributed to the Covid crisis. While this is unlikely to be strictly accurate, it seems plausible that the Covid crisis accounts for most of the unusual variation in these series in the first half of 2020.

Identification comes from the fact that demand-side and supply-side disturbances have different implications for industry-level production and inflation. So, given price and quantity data for these industries in the first two quarters of 2020, it is possible to identify the disturbances that have driven their changes.

Figure 3 shows the aggregate disturbances that the model requires to match data observed data in the first half of 2020.[22]

**Figure 3: Aggregate disturbances during the Covid crisis**




Source: Author's calculations.

The left panel shows the implied decline in aggregate productivity (outside of customer-facing services

[19]Because I am working with a closed economy model, I estimate the structural changes for each economy independently of the changes that occurred in other economies.
[20]For China I target fixed asset investment and consumer price inflation as quarterly investment and consumption deflator data are not publicly available.
[21]Appendix A explains how I assign consumption data to each industry.
[22]I show the average of the disturbances in 2020Q1 and 2020Q2.

industries). This was largest, at around 6% in Europe. The decline was around 3% in the US, 2% in China and around 0.5% in Japan.

The middle column shows the implied consumption disturbances. These can roughly be thought of as the declines in steady-state consumption that would have occurred absent any price or income changes. This was around 10% in the EA and China, 5% in the US and a bit under 3% in Japan.

The right column shows the implied increase in required returns on capital. This was largest, at slightly over 1 percentage point in the US, but smaller in the other three economies.

A natural question is how plausible these estimates are? In the case of the EA, US and Japan, the estimates of the supply disturbances are consistent with the relative stringency of lockdown measures, as well as with the relative impact of the virus in terms of number of cases and deaths (allowing for large regional variation within the US and the EA). The estimate of the increase in required capital returns is also consistent with the largest financial disruptions in the first half of 2020 occurring in corporate bond markets, which are a more important source of funding for firms in the US than in the EA or Japan.

The estimates for China are not strictly comparable to those of the other economies as the outbreak of the virus, and associated economic contraction, occurred earlier there. Nevertheless, the relative importance of supply and demand factors is consistent the evidence to hand that the recovery in economic activity since 2020Q2 has been concentrated in investment, trade and public demand. In contrast, consumption has been slower to recover.

Figure 4 shows the estimated industry-specific productivity disturbances during the Covid crisis. These were generally negative for all of the industries. For the US, EA and Japan, the declines in productivity in the recreational industry and social services industry were generally larger than for the economy as a whole. The picture is less clear for the other three industries. For Japan, declines in productivity in the retail, transport and other services industries were larger than the aggregate economy. However, for the US, the declines in productivity were somewhat smaller. In the EA, the declines in productivity in these industries were similar to those elsewhere in the economy.

For China, the estimated supply disturbances in customer-affected service industries were considerably larger than for the economy as a whole. This is again consistent with anecdotal evidence that, while manufacturing and construction firms were able to resume activity relatively soon after the peak of the crisis, firms in consumption-focussed industries have faced more persistent constraints.[23]

Figure 5 shows the estimated demand disturbances during the first half of 2020. These can be interpreted as the estimated percentage changes in demand for each sector's output, absent any price changes or aggregate disturbances.

For all economies, demand for recreational services declined 20-40%, while transport and social services also experienced large demand disruptions. In contrast, outside of China the estimated decline in retail trade demand was much smaller, and in fact is estimated to have increased in Japan. This is consistent with the idea that the crisis led to a re-allocation of retail demand towards online purchases, rather than an overall decline in demand for retail products. In China, the decline in retail trade demand was larger.

[23] For example, see The Economist (2020b).

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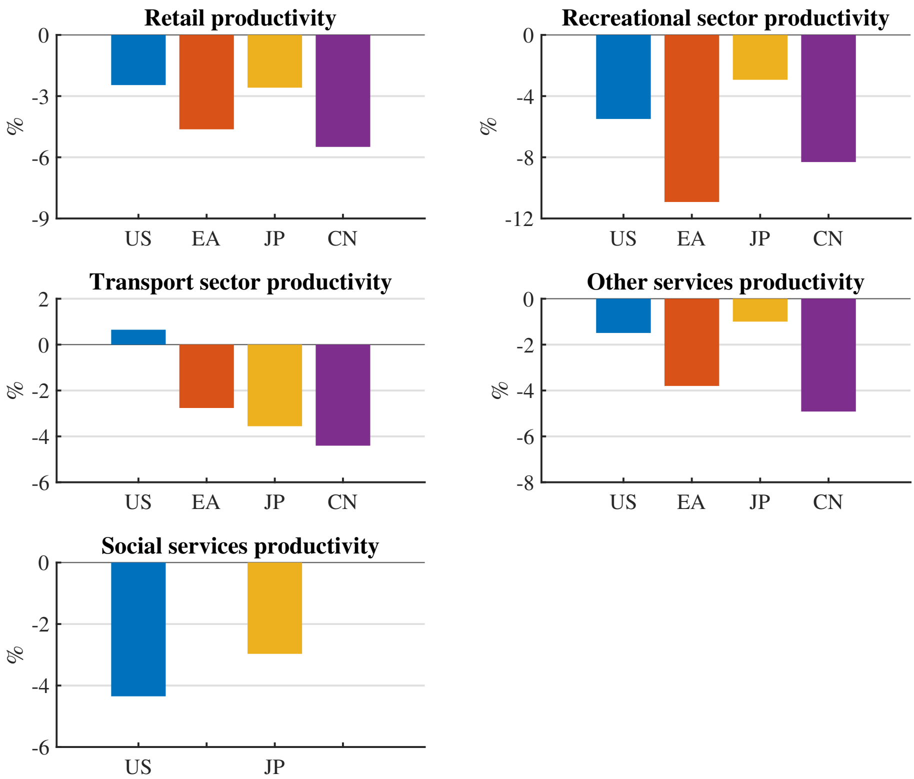
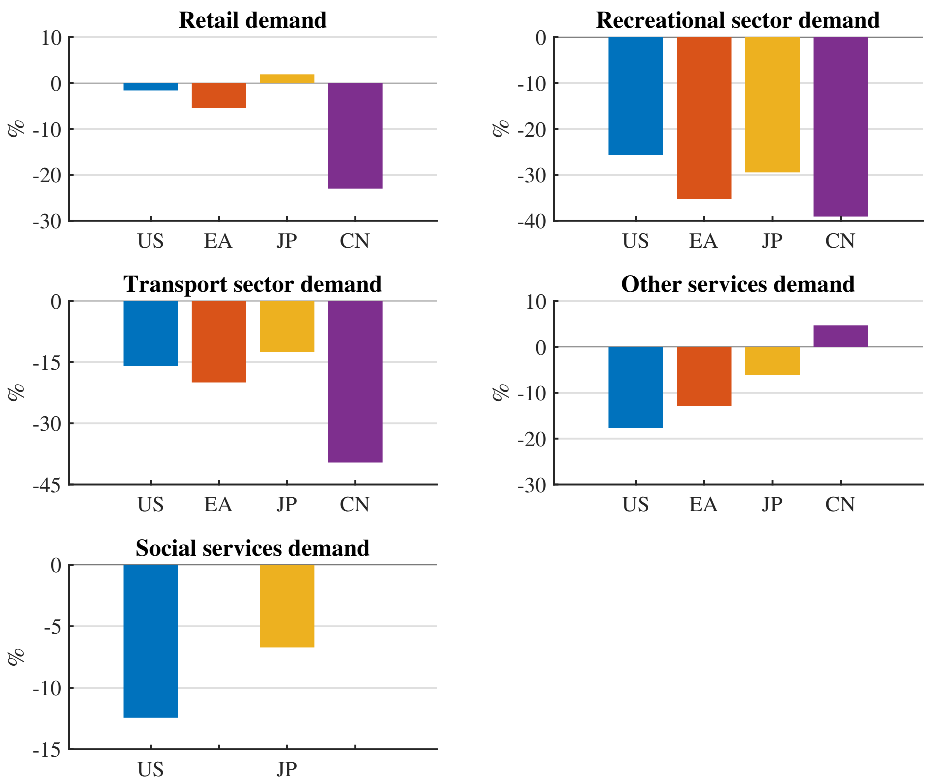



Source: Author's calculations.

In sum, the results in this section suggest that, at an aggregate level the decline in activity due to the Covid crisis reflects a combination of supply-side and demand-side factors. Customer-facing industries experienced particularly large declines in activity. This reflects more stringent constraints on business practices, particularly in recreation and social services industries, and a shift in consumption preferences away from these services. Using these estimates, I now turn to what these disturbances imply for the recovery from from the crisis.

## 4 Scenarios for the Recovery

I model three scenarios for the recovery. For each, I assume that the aggregate disturbances that occurred in the first half of the year decay by 50% each quarter. This is consistent with the easing of stringent lockdown measures over recent months. This assumption means that the direct effects of the aggregate disturbances on economic activity largely dissipates by early 2021. However, these disturbances continue to exert an indirect effect on economic activity through the inherent amplification and persistence mechanisms in the model.




Source: Author's calculations.

I then consider three scenarios for customer-facing service industries:

1. Baseline: 50% of the idiosyncratic disturbances to these industries turn out to be persistent and remain in place until mid-2023.

2. Optimistic: 25% of the idiosyncratic disturbances to these industries are persistent and remain in place until mid-2021.

3. Pessimistic: 75% of the idiosyncratic disturbances to these industries are persistent and remain in place until mid-2025.

I present first the aggregate model projections and then turn to the industry-level implications, including the role of cross-industry spillovers.

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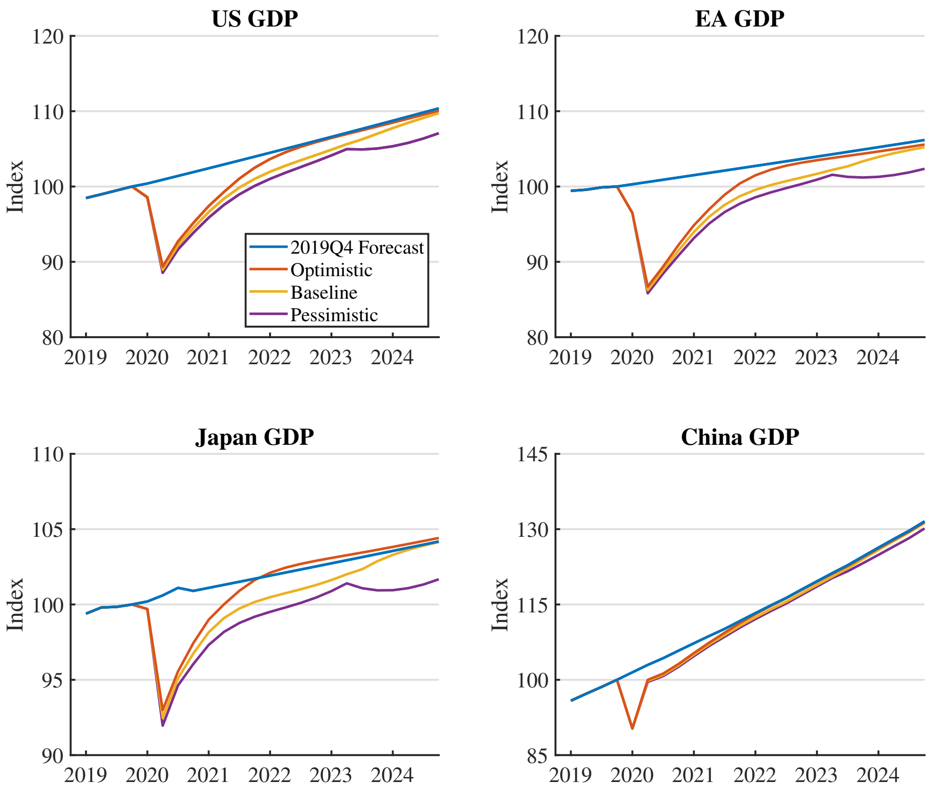
### 4.1 Key results

Figure 6 shows projections for the level of real GDP for the four economies. In each panel, the blue line shows the GDP projections implied by the median Consensus Economics growth forecast in 2019Q4. I take this to be the counterfactual path for GDP in the absence of the pandemic. The yellow line shows the path of GDP under the baseline scenario. The red and purple lines show the projections under the optimistic and pessimistic scenarios.

**Figure 6: GDP projections**




Source: Author's calculations; Consensus Economics.

In the baseline scenario the US, GDP and Japan experience a persistent shortfall in economic activity. Output grows quickly in the second half of 2020. But the pace of recovery then slows and GDP does not return to its 2019Q4 level until early 2022. Even then, all three economies face a '98% economy' as output stagnates persistently 2% below its pre-crisis trend for several years.

In the near-term, the path of output under the optimistic scenario is similar to the baseline scenario. However, in the optimistic case the robust economic recovery continues into 2021, alongside the easing in constraints on customer-facing service industries in the second half of that year. By early 2022 GDP has returned to its pre-crisis trend.

In contrast, in the pessimistic scenario, the US, EA and Japan face a persistent slump. In this scenario, these economies face a 95% economy, with output persistently 5% below its pre-crisis trend.

The recovery in China proceeds faster. Although the model anticipates that growth will slow somewhat in the second half of 2020, GDP returns near its pre-crisis trend by mid 2021. There is also relatively little difference between the three scenarios for China. This reflects two factors. First, the rapid growth that occurred in 2020Q2 means that there is less ground to make up. Second, the calibration attributes more of the decline in customer-facing service industries to aggregate disturbances and industry-specific demand disturbances, than for the other three economies.

Figure 7 shows the implications of the forecasts for year-on-year GDP growth in the calendar years 2020, 2021 and 2022. It also compares these figures to the the median Consensus Forecast from September 2020. Relative to Consensus, the model based forecasts for the US, EA and China point to weaker GDP growth in 2020, but a faster recovery in 2021.[24] For Japan, the year-on-year growth profiles in the baseline scenario are close to the Consensus Forecasts. For all economies, the level of GDP at the end of 2021 in the model-based scenarios is similar to that implied by the Consensus Forecast profile. This largely reflects the easing of aggregate constraints on activity. The lingering constraints on customer service industries are most keenly felt in 2022, when *growth* in the AEs is projected to revert to something close to its long-term trend. This leaves a persistent gap between the projected *level* of GDP and its pre-Covid trend in these economies.

### 4.2 Supply- and demand-side determinants and potential output

The calibration attributes the contractions in GDP in the first half of 2020 to a combination of demand- and supply-side factors. To illustrate the implications of these two sets of forces for the recovery, Figure 8 shows GDP projections that isolate the effects of supply- and demand-side disruptions separately. The lines labelled 'Only supply disturbances' show GDP projections constructed by feeding only the estimated changes in aggregate- and industry-specific productivity into the model. The lines labelled 'Only demand disturbances' show GDP projections constructed by feeding only the changes in aggregate and industry-specific consumption preferences into the model.[25]

Both sets of disturbances contributed to the decline in activity in the first half of 2020. However, the contraction in GDP induced by supply disturbances is quantitatively larger and more persistent for each economy. Absent supply disturbances, these economies would face sizeable, but by no means unprecedented, recessions. The ongoing constraints on supply in consumer-facing service industries make the downturns unusually deep and persistent.

Another way to view the economic forces driving the recovery is to compare the model's output projections to its estimates of potential GDP. Of course, the concept of 'potential output' is far from clear in an environment where government restrictions, and individual behavioural responses, are directly constraining economic activity. For this exercise, I use the standard approach in the DSGE literature and define

[24] Because these forecasts include the same information about GDP growth in the 2020Q1 and Q2, this implies that the model-based forecasts project slower GDP growth in the second half of 2020.

[25] In both sets of projections, I omit the aggregate disturbances to the return on capital and government demand. The aggregate effects of these disturbances are generally small relative to the other disturbances.

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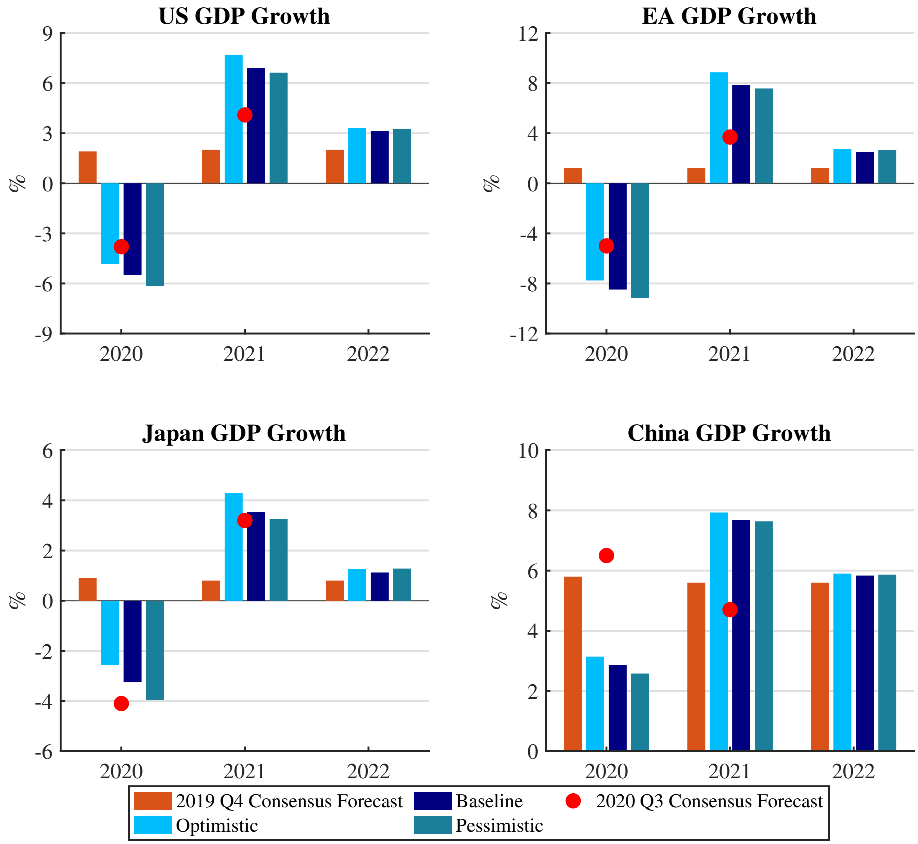
Figure 7: GDP growth projections



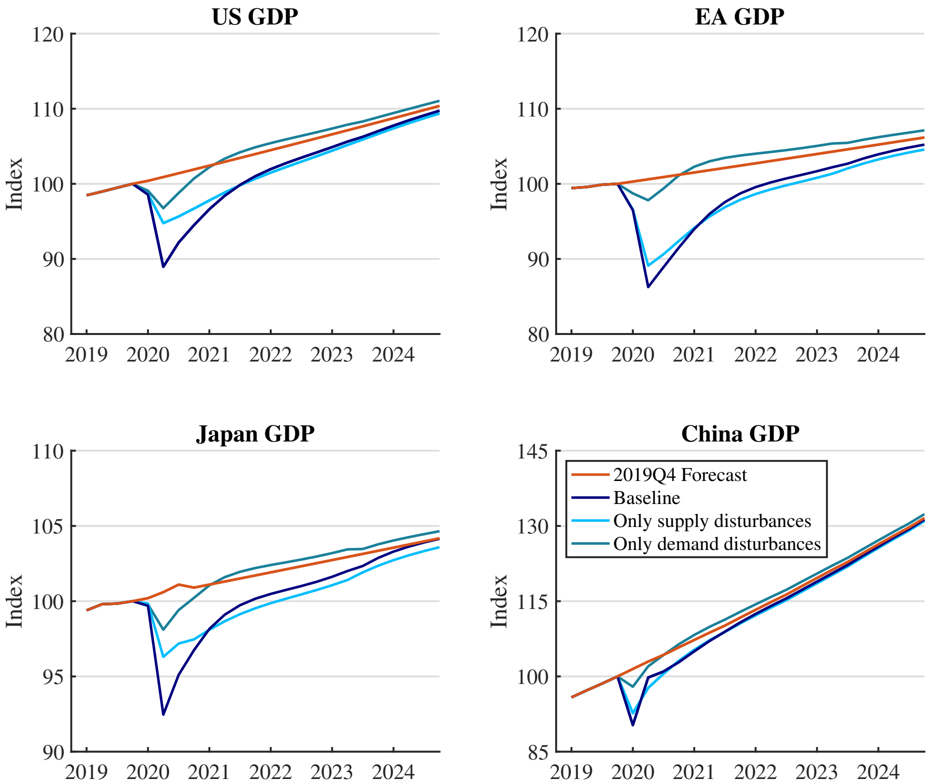

Source: Author's calculations; Consensus Economics.

potential output as the level of GDP that would occur if an economy experienced the same sequence of economic shocks and structural changes but all prices and wages were flexible. This represents a measure of potential output conditional on the administrative restrictions and behavioural changes induced by the pandemic. The model is silent on whether these constraints are appropriate.

Figure 9 compares the model's baseline GDP projections to its estimates of potential output. All variables are expressed in percent deviations from their pre-Covid trends.[26] For all four economies, the model attributes most of the decline in economic activity in the first half of the 2020, and almost all of the ongoing shortfall of GDP below its pre-crisis trend, to a lower level of potential output. This accords with the common-sense view that the Covid crisis reflects policy and behavioural responses to a health crisis, with little role for price and wage ridity in shaping economic outcomes. Nonetheless, the model expects output to be somewhat below potential in the coming years in the US and Japan, suggesting an ongoing role for demand management policy in shaping economic outcomes in the near-term. In contrast, the

[26]The model does not tell us what the output gaps in these economies would have been in the absence of the Covid crisis.

**Figure 8: GDP projections: demand and supply-side disruptions**




Source: Author's calculations; Consenus Economics.

model estimates indicate that output is likely to be close to potential in the EA and China.

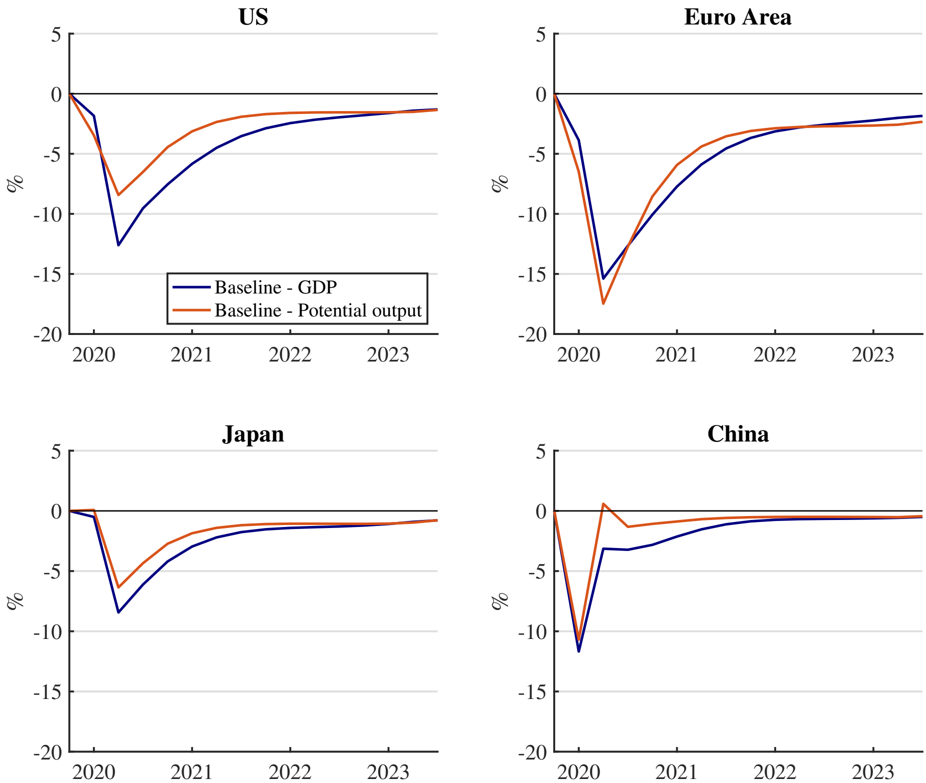
### 4.3 Industry-level implications

The ongoing slump in aggregate economic activity is likely to be profoundly uneven in its industry composition. To illustrate this, Figure 10 shows industry-level value-added projections for the baseline scenario in the EA and China. The results for Japan and the US are similar to those for the EA. In the graph, I group the industries into four broad categories: customer-facing industries, primary industries, goods industries and other services industries.[27] The lines are scaled to show the output of each industries in percent deviations from their pre-crisis trend.

Customer-facing service industries experience a large and persistent depression. In the EA, output in these industries contracted by 25% in the first half of 2020. Moreover, under the assumptions of the scenario,

[27] Customer facing industries include recreation services, retail trade, transport, social services and other services. Primary industries include agriculture and mining. Goods industries include construction, utilities, manufacturing and wholesale trade. Other services industries include transportation, information services, business services and government services.

**Figure 9: GDP projections and potential output**




Source: Author's calculations.

their output is projected to remain more than 10% below their pre-crisis trends until the end of 2022. Other sectors of the economy also experienced a sharp contraction in activity in the first half of 2020. However, conditions in these industries are expected to recover more quickly and, by the end of 2022, be close to their pre-crisis trend. In China, output in customer-facing service industries remains more than 5% below its pre-crisis trajectory for several years after output in other industries fully recovers.

The declines in industry output reflect a number of forces. These include changes in aggregate demand, shifts in relative prices and preferences, and changes in the demand for goods as an intermediate input into production. Figure 11 shows the relative importance of these forces for the four industry groups used in Figure 10 for the EA.[28] In the Figure, I decompose changes in industry value added into three factors: income effects due to changes in the aggregate level consumption, investment and public demand, substitution effects due to shifts in preferences and relative prices and changes in demand for goods as intermediate inputs.[29]

[28] Results for the other economies are qualitatively similar.

[29] Industry value added is also affected by changes in the volume of intermediate inputs used as a production *input*. Because the industry production functions are independent of the final destination of the output, I allocate the intermediate inputs proportionally to the income, substitution and intermediate components of industry gross output. Appendix B describes the

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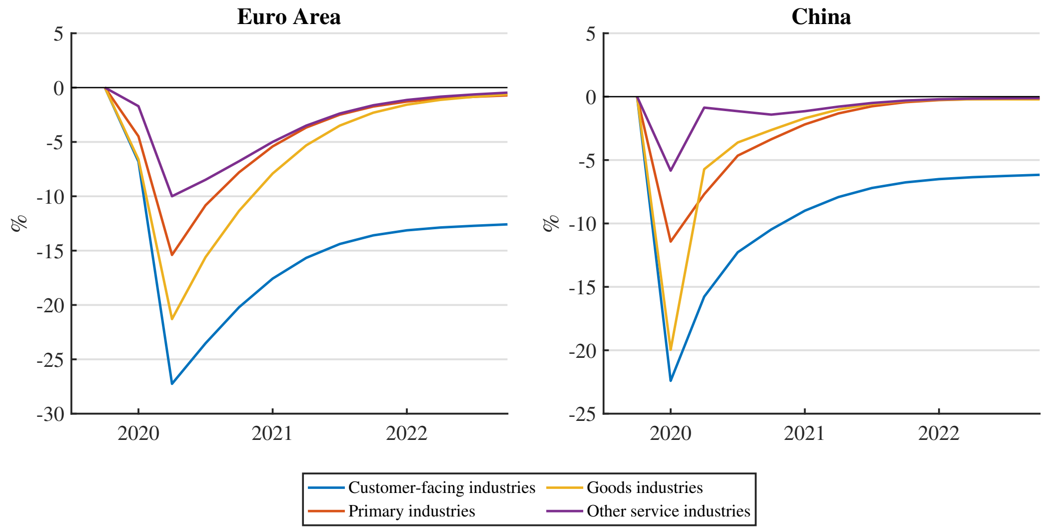
**Figure 10: Industry value-added**

Percent deviation from pre-Covid trend




Source: Author's calculations.

The decline in output in customer facing services industries reflects all three of these forces listed above. Lower demand for final goods and services exerts a negative income effect. Adverse shifts in customer preferences and higher relative prices for these services represents a negative substitution effect. And the lower level of aggregate demand lowers demand for these services as an input into production. Income effects also lower the output of other industries, although by somewhat less given the smaller share of output of these industries devoted to servicing final demand. In contrast, substitution effects contribute to higher output, as other industries benefit from preference shifts away from customer-facing services. Reduced demand for intermediate inputs contributes particularly to lower output in goods and primary industries. This illustrates the importance of account for input-output linkages to fully understand the effects of the Covid crisis at the industry level.

Recessions commonly involve large contractions in a small number of cyclically sensitive industries. However, the extent of the dispersion in the Covid crisis is unusually large. To illustrate this, I calculate an industry dispersion growth index as in Lilien (1982). Let $s_{i,t-j}$ be industry $i$'s share of gross value added at time $t-j$, $g_{i,t-j,t}$ be the growth rate of value-added in industry $i$ between $t-j$ and $t$ and $g_{t-j,t}$ be the growth rate of GDP between $t-j$ and $t$. The industry output dispersion index is:

$$R_t = \sqrt{\sum_{i=1}^{\mathcal{F}} s_{i,t-j} \left( \frac{g_{i,t-j,t}}{g_{t-j,t}} - 1 \right)^2} \tag{16}$$

The measure $R_t$ will take a value between 0 and 1, with a larger value indicating more growth dispersion.

decomposition in more detail.

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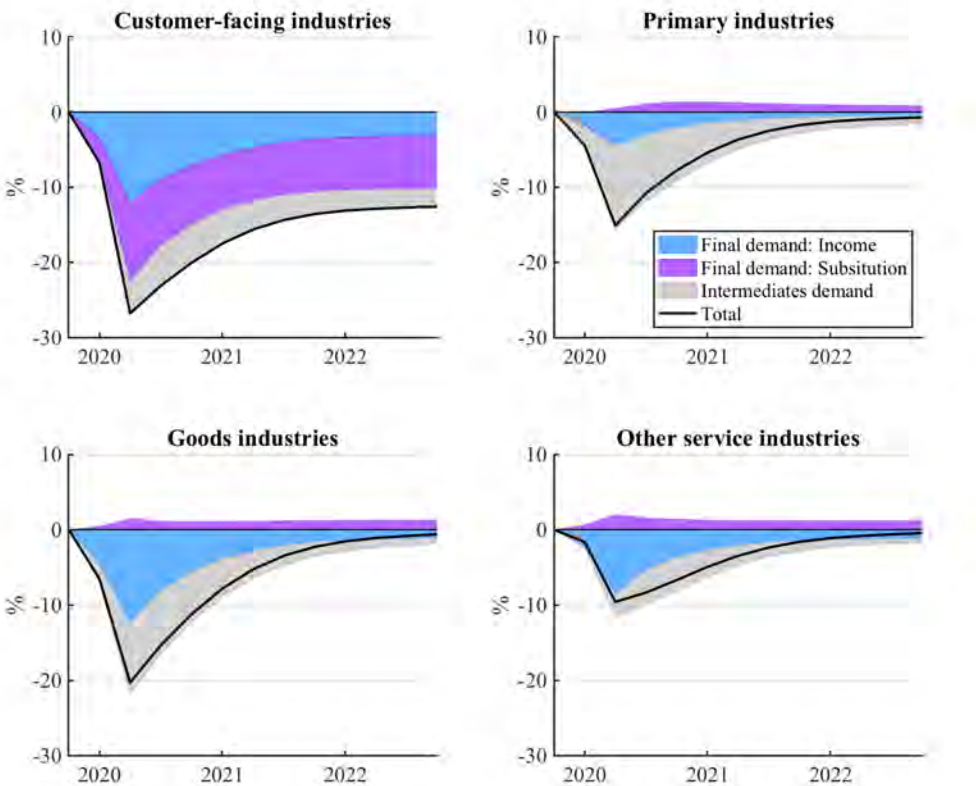
**Figure 11: Industry value-added: Euro Area**
Percent deviation from pre-Covid trend




Source: Author's calculations.

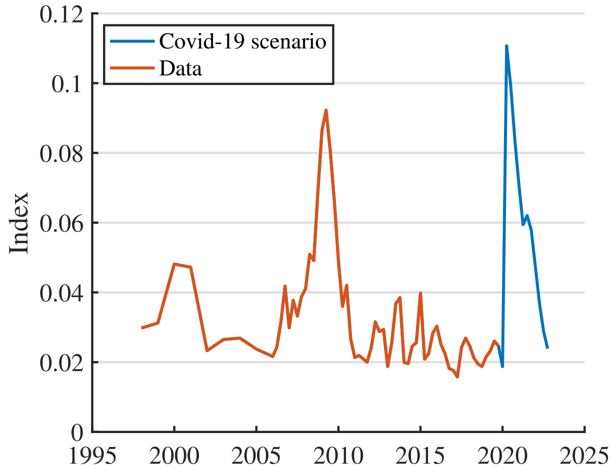
Graph 12 shows the index for the US, calculated setting $j = 4$.[30] The peak in industry growth dispersion is larger than during the GFC. Moreover, dispersion is projected to stay elevated until 2023. This may well understate the extent of industry growth dispersion over this time as it assumes no additional aggregate or industry-specific shocks.

Figure 13 gives another perspective on the changes in industry composition that could occur over the next few years. The top left panel plots the projected changes in the share of industries in value-added for the US under the baseline scenario. The other three panels plot the changes that occurred around the three most recent US recessions: the Great Financial Crisis (GFC), the early 2000s tech bust and the recession of the early 1990s.

The extent of persistent industry re-allocation induced by the Covid-19 recession in the US is similar to that which occurred in the GFC. For example, the model anticipates that three industries - social services,

[30] The index before 2006 is calculated using the dispersion of annual average growth rates, setting $j = 1$. From 2005, the index is calculated using quarterly growth rates.

**Figure 12: US Industry Output Growth Dispersion Index**




Source: Author's calculations.

recreation services and finance & real estate services - will experience persistent changes in their GDP shares of more than 0.5 percentage points over the next few years. During the GFC four industries - construction, manufacturing, social services and government services - experienced such persistent changes (although some industries, such as financial services, experienced large but less persistent changes).[31] The number of industries whose GDP share changes by more than 0.5 percentage points is at least as large as occurred following the tech bust and the 1990s recession. As in the previous example, this exercise could understate the amount of reallocation that is likely to occur as it abstracts from reallocation driven by factors other than the Covid crisis.

Another difference between the Covid crisis and past recessions is that much of the reallocation is likely to occur within the services sector. According to the model, the shares of social services and recreation services in US GDP could decline by around 1/2 percentage point over the next few years. This could be offset by an increase in the shares of real estate services and, to a lesser extent, government services. The shares of retail trade and manufacturing in value added are also expected to rise somewhat. In contrast, during the GFC-induced structural change was felt most strongly in the goods sector, at least in the US. The shares of construction, retail trade and manufacturing in GDP declined (although the latter was largely the continuation of a long-term trend). Meanwhile, the shares of social, government and professional services in GDP increased. The finance sector experienced a large decline in its GDP share in 2008, but recovered most of that ground in 2009. The early 1990s recession was also characterised by a decrease in the share of goods production in GDP and a rise in the share of services.

[31]Moreover, some of these changes, such as the decline in the manufacturing share of GDP, reflect long-run trends arguably unrelated to business cycle conditions.

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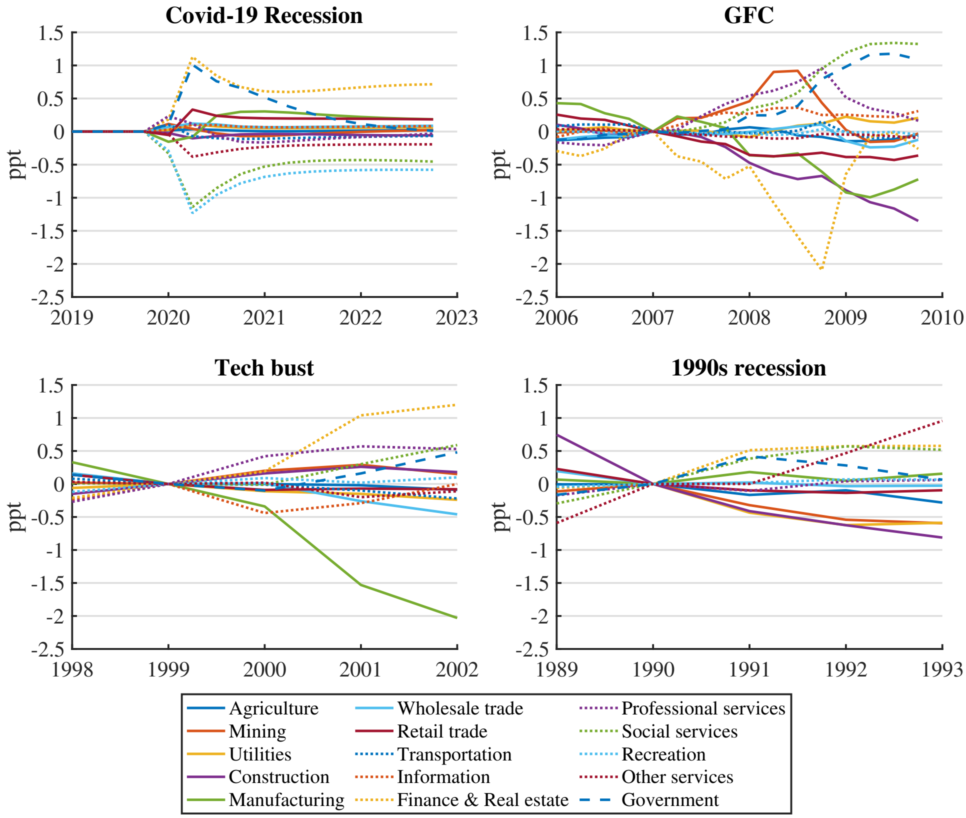
**Figure 13: Change in industry value-added shares around US recessions**




Source: Author's calculations; Bureau of Economic Analysis.

## 5 Related literature

A large literature on the characteristics and economic consequences of the Covid crisis has emerged over recent months. This paper is related to three strands of this literature.

The first strand explores whether the Covid crisis is best thought of as representing a demand-side or supply-side disturbance. Papers in this literature tend to focus exclusively on economic developments in the US. For example, Baqaee and Farhi (2020) build a multi-industry model general equilibrium model similar to the one used in this paper and use it to estimate the demand and supply shocks that explain industry-level output growth outcomes in the US in 2002Q2. Brinca et al. (2020) estimate labour supply and labour demand shocks at an industry level during the peak of the crisis in March, April and May US using a Bayesian VAR model. Both papers attribute the decline in US activity in the first half of 2020 to a combination of supply- and demand-side disturbances but conclude that on net, supply-side disturbances have exerted a larger influence on economic activity.

The second strand of the literature seeks to quantify the broader macroeconomic consequences of the

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pandemic. A key paper in this literature is McKibbin and Fernando (Forthcoming), who use a large multi-industry multi-region macroeconomic model to simulate the effects of a global pandemic on GDP growth in 2020 under a number of different scenarios. Others include Kohlscheen et al. (2020), who explore the international spillover effects of the pandemic, and Deb et al. (2020) who estimate the economic effects of containment measures.

The third strand of the literature explores the macroeconomic consequences of economic disturbances at the industry level.[32] Many of these papers, including Guerrieri et al. (2020), Faria-e-Castro (2020) and Bodenstein et al. (2020) use two or three industry models to examine how disruptions in one part of the economy influence economic conditions in other industries. An exception Kaplan et al. (2020), who use a richer multi-industry Heterogeneous Agent New Keynesian (HANK) model calibrated at the two-digit ISIC level, quantify the effect of alternative containment and fiscal strategies in the US.

The current paper extends the existing literature in several respects. One contribution is to estimate the contribution of demand- and supply-side disturbances to aggregate economic activity for three other large economies, whose experiences of the virus differed greatly from the US. The paper extends the literature on industry-level disturbances by integrating these disturbances into a macroeconomic model with a richer set of rigidities and frictions, allowing for more realistic quantitative predictions of how these disturbances could affect economic activity. In addition, the paper extends the current literature by looking beyond the near-term determinants of the Covid crisis and providing scenarios for how the economic disturbances associated with the crisis could play out in the years ahead.

## 6 Conclusion

The economic consequences of the Covid crisis will be felt for many years to come. Using a multi-industry general equilibrium model, I find that ongoing disruptions to customer-facing service industries could see the US, EA and Japan face a '98% economy', even if the economy-wide disturbances associated with the pandemic recede relatively quickly. Output in customer-facing service industries could remain 10-20% below its pre-Covid trajectory if ongoing constraints on work practices remain in place for three years. For China, the results point to a faster and more complete economic recovery. But even there, the recovery is projected to occur unevenly across industries.

The results of this paper have several implications for policy. The likelihood of large and persistent changes in industrial composition highlights the necessity of striking a balance between sustaining productive firms and employer-employee matches and fostering the reallocation of resources that may be required as a result of the pandemic. The importance of supply-side disturbances in driving the shortfall in activity relative to its pre-crisis trajectory also highlights the limits of demand-management policy in managing the fallout from the crisis. While ongoing policy stimulus will likely be necessary, a full economic recovery will require us to either contain the virus or find a way to live with it. Finally, the persistent slump, and its highly uneven sectoral distribution has implications for financial stability policy. The large contraction in economic activity is likely to see corporate bankruptcies rise in many economies over the coming years Banerjee et al. (2020). These bankruptcies could be particularly concentrated in those industries particularly affected

[32] Examples that pre-date the Covid crisis include Horvath (2000) and Atalay (2017).

by the pandemic, leading to elevated risks for financial institutions heavily exposed to those sectors.

There are a number of issues this paper has not considered. I have worked with a closed economy model that abstracts from from cross-border trade and financial spillovers. For large economies where trade in customer-facing services accounts for a relatively small share of output this may be a reasonable assumption. However, to examine the economic consequences of the pandemic for smaller economies, particularly those with large tourism or education sectors, it would be important to extend the model to incorporate international spillovers. The model also features a relatively sparse financial system. As such, it is not well placed to account for the economic consequences of higher private and public debt levels or increased firm bankruptcies, that could result from the pandemic. Accounting for these developments could lead to larger estimates of the macroeconomic consequences of the pandemic than presented here. Finally, the estimates of the substitutability of goods and services in production and consumption are based upon average relationships estimated under normal economic conditions. The large and abrupt changes in production and consumption patterns induced by the Covid crisis could be more costly than those which occur during normal times. Better understanding how firms and households are navigating the changes in induced by the Covid crisis at a microeconomic level would help be a useful avenue for future research.

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## A Data sources

This appendix describes the data sources used to calibrate the input-output structure of the model as well as the Covid-scenario.

### United States

*Input-output structure*

Input output data is sourced from the Bureau of Economic Analysis (BEA) 2019 input output tables at the 1-digit NAICS level. I drop the non-comparable imports and second hand scrap sectors.

*Covid scenario*

I source the four aggregate data series - GDP, personal consumption expenditures (PCE), gross fixed capital formation and the personal consumption expenditure deflator from the BEA national accounts. I then use the BEA PCE bridge to map changes in the PCE quantity and price indices into changes in consumption at the industry level.[33]

### European Union

*Input-output structure*

Input-output data is sourced from the Eurostat 2015 input-output tables.

*Covid scenario*

I source the four aggregate series - GDP, household final consumption expenditure, gross fixed capital formation and the consumption deflator from the Eurostat national accounts.

Eurostat does not publish consumption data at a sufficiently disaggregated level to allow for estimates of EA industry-level consumption. I therefore rely on German and French household consumption expenditure estimates, published by the German Federal Statistical Office and INSEE to estimate these values. For Germany, I calculate recreation consumption as the sum of "Recreation, entertainment and culture" expenditure and "Accommodation and restaurant services" expenditure. I calculate retail expenditure as the sum of "Food, beverages and tobacco products", "Clothing and footwear" and "Furniture, lighting equipment, appliances etc." Price and quantity data are available for all of the series. For France, industry-level consumption data in real and nominal terms are directly available for all of the industries in the model.

For each industry-level consumption series, I construct a Euro-area price and quantity index by taking an equally-weighted average of the growth rates of the German and French series. The German economy is larger than the French economy, and hence accounts for a larger weight in overall EA consumption. However, the German economy was also less affected by the Covid crisis than most other economies in the Euro area. Applying equal weights to Germany and France, which was more affected by the pandemic,

[33] The PCE bridge is available at `https://apps.bea.gov/industry/xls/underlying-estimates/PCEBridge_1997-2018_SUM.xlsx`.

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helps to account for this.

### Japan

*Input-output structure*

Input-output data is sourced from the Statistics Bureau of Japan's (SBJ) 2015 input-output tables.

*Covid scenario*

I source the four aggregate series - GDP, household final consumption expenditure, gross fixed capital formation and the consumption deflator from the SBJ's national accounts.

As for the EA, the SBJ national accounts do not publish household consumption data at a sufficient degree of aggregation to allow for estimates of industry-level consumption in Japan. I estimate retail trade consumption using the Retail Sales data release. I estimate the other customer-facing services components using estimates from the Japan Services Industry Survey data release. Recreation services are the sum of the series "Accommodation, eating and drinking services" and "Living-related and personal services and amusement services". Transport services are equal to the series "Transport and postal activities". Social services are equal to the sum of the series "Education, learning support" and "Medical, health care and welfare". Other services are equal to the series "Services n.e.c.".

The retail trade and services data are available only in nominal terms. I use data from the Japanese Consumer Price Index (CPI) to construct price indices for these series. I use these series to construct industry-level inflation rates and use these to deflate the nominal consumption expenditure data defined above. I define the retail trade price index as a weighted average of the indices for "Fresh Food", "Furniture and household utensils", "Clothes and footwear", "Recreation goods", and "Domestic non-durable goods".[34] The transportation price index is the CPI category "Transportation and communications". The recreation services price index is the CPI category "Culture and recreation". The other services price index is a weighted average of the categories "Domestic services", "Repairs and maintenance" and "Personal care services". A series of policy changes led to large decreases in the Education component of the CPI in October 2019 and April 2020, which makes this series an unreliable guide to demand conditions in the social services sector. I therefore use the aggregate CPI as the measure of education prices.

### China

*Input-output structure*

I construct input-output relationships for China using information from the Asian Development Bank's Multiregional Input-Output Database and the National Bureau of Statistics of China (NBSC) input-output tables, in both cases for 2015. Because the ADB tables contain more industry detail, particularly for services industries, I use this datables to construct the intermediate-input use and final use matrices. I use the NBSC database to seperate industry value added into compensation of employees and gross operating surplus, as this information is missing from the ADB database.

[34] I use relative CPI weights to construct the weighted average.

*Covid scenario*

The source for all data series is the NBSC. I seasonally adjust all data series using the X-12 procedure.

Quarterly aggregate GDP is available directly from the national accounts. For consumption expenditure I use the series "Consumption Expenditure of Urban Households". For investment I use the series "Fixed Asset Investment". My measure of consumption inflation is the consumer price index. For China I use measures of value-added by industry, rather than household consumption. For the transport industry I use the series "Value added by Transport, Storage and Post". For the retail trade industry I use the series "Value added by Wholesale and Retail Trade". For the recreation industry I use the series "Value added by Accommodation and Catering Trade". For other services I use the series "Value added by Other".

I construct industry-level inflation using data from the Chinese Consumer Price Index (CPI). For retail trade I use the series "Clothing". For transportation I use the series "Transportation and Communication". For recreation I use the series "Education, Culture and Recreation". For other services I use the series "Miscellaneous Goods and Services".

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## B Structural change algorithm

This appendix describes the sequence of structural changes that I use to account for the Covid crisis and its aftermath.[35]

Up to and including 2019Q4 the structure of the economy is described by the system of equations:

$$\mathbf{A}x_t = \mathbf{C} + \mathbf{B}x_{t-1} + \mathbf{D}\mathbb{E}_t\{x_{t+1}\} + \mathbf{F}\varepsilon_t \tag{B.1}$$

where $x_t$ is the vector of model variables and $\varepsilon_t$ is a vector of exogenous i.i.d. shocks. The matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{D}$ and $\mathbf{F}$ are the equation coefficients consistent with the initial structure of the economy.

If it exists and is unique, the standard rational expectations solution to Equation (B.1) is the VAR:

$$x_t = \mathbf{J} + \mathbf{Q}x_{t-1} + \mathbf{G}\varepsilon_t \tag{B.2}$$

where the reduced form matrices $\mathbf{J}$, $\mathbf{Q}$ and $\mathbf{G}$ are constant, consistent with the stable economic structure.

In 2020Q1, the economic structure changes to:

$$\bar{\mathbf{A}}x_t = \bar{\mathbf{C}} + \bar{\mathbf{B}}x_{t-1} + \bar{\mathbf{D}}\mathbb{E}_t\{x_{t+1}\} + \bar{\mathbf{F}}\varepsilon_t \tag{B.3}$$

where $\bar{\mathbf{A}}$, $\bar{\mathbf{B}}$, $\bar{\mathbf{C}}$, $\bar{\mathbf{D}}$ and $\bar{\mathbf{F}}$ are the equation coefficients consistent with the structure of the economy that prevailed in 2020Q1.

I assume that in 2020Q1 agents expected the economic structure to be temporary and revert to its initial structure in 2020Q2. In this case, the reduced form solution is:

$$x_t = \bar{\mathbf{J}} + \bar{\mathbf{Q}}x_{t-1} + \bar{\mathbf{G}}\varepsilon_t \tag{B.4}$$

where:

$$\bar{\mathbf{J}} = \left(\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}\right)^{-1}\left(\bar{\mathbf{C}} + \bar{\mathbf{D}}\mathbf{J}\right) \tag{B.5}$$

$$\bar{\mathbf{Q}} = \left(\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}\right)^{-1}\bar{\mathbf{B}} \tag{B.6}$$

$$\bar{\mathbf{J}} = \left(\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}\right)^{-1}\bar{\mathbf{F}} \tag{B.7}$$

where $\bar{\mathbf{Q}}$ and $\bar{\mathbf{J}}$ are the reduced form solution matrices from Equation (B.2).

In 2020Q2 and 2020Q3, the structure of the economy changes once more. The latter structure prevails until some future period $\mathbf{T}$. These changes are anticipated in 2020Q2. For these periods, the reduced form solution matrices can be calculated recursively.

Specifically, assume that the structure of the economy prevailing between 2020Q3 and $\mathbf{T}-1$ is:

$$\tilde{\mathbf{A}}x_t = \tilde{\mathbf{C}} + \tilde{\mathbf{B}}x_{t-1} + \tilde{\mathbf{D}}\mathbb{E}_t\{x_{t+1}\} + \tilde{\mathbf{F}}\varepsilon_t \tag{B.8}$$

[35] A description of these approaches in a more general setting is available in Kulish and Pagan (2017).

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where $\tilde{\mathbf{A}}$, $\tilde{\mathbf{B}}$, $\tilde{\mathbf{C}}$, $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{F}}$ are the equation coefficients consistent with the structure of the economy that prevail from 2020Q3. And assume that agents expect that at some future period $\mathbf{T}$ the economy will revert to the economic structure that prevailed prior to the crisis. The solution to the model between 2020Q3 and $\mathbf{T}$ is a time-varying VAR of the form:

$$x_t = \mathbf{J}_t + \mathbf{Q}_t x_{t-1} + \mathbf{G}_t \varepsilon_t \tag{B.9}$$

where the time-varying reduced form matrices are given by:

$$\mathbf{J}_t = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}_{t+1})^{-1}(\bar{\mathbf{C}} + \bar{\mathbf{D}}\mathbf{J}_{t+1}) \tag{B.10}$$

$$\mathbf{Q}_t = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}_{t+1})^{-1}\bar{\mathbf{B}} \tag{B.11}$$

$$\mathbf{G}_t = (\bar{\mathbf{A}} - \bar{\mathbf{B}}\mathbf{Q}_{t+1})^{-1}\bar{\mathbf{F}} \tag{B.12}$$

As we know the values of $\mathbf{Q_T}$ and $\mathbf{J_T}$, one can solve this system of equations recursively to derive the sequence of reduced form matrices from the start of the crisis to its resolution.

The solution for the reduced form solution matrices in 2020Q2 is a straightforward application of the recursions defined above to the economic structure that applies in 2020Q2.

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## C Industry value-added decomposition

This appendix describes the decomposition of industry-value added in Section 4.3.

I start with the definition of industry value-added:

$$\underbrace{y^{va}_{j,t}}_{\texttt{Value-added}} = \underbrace{c_{j,t} + i_{j,t} + g_{j,t}}_{\texttt{Final demand}} + \underbrace{\sum_{k}^{\mathcal{F}} x_{k,j,t}}_{\substack{\texttt{Intermediates}\\ \texttt{demand}}} - \underbrace{\sum_{k}^{\mathcal{F}} x_{j,k,t}}_{\substack{\texttt{Intermediate}\\ \texttt{inputs}}} \tag{C.1}$$

where the second term from the right refers to demand for the output of good $j$ as an intermediate input and the final term refers to intermediate inputs used in the production of good $j$.

Define $fd_{j,t} = c_{j,t} + i_{j,t} + g_{j,t}$ as the final demand for the output of industry $j$. Using the fact that in the initial steady state all relative prices equal 1, I define the income component of final demand as:

$$fd^{y}_{j,t} = \omega_{c,j} C_t + \omega_{i,j} I_t + \omega_{g,j} G_t \tag{C.2}$$

where $\omega_{c,j}$, $\omega_{i,j}$ and $\omega_{g,j}$ are the weights of the output of industry $j$ in the aggregate consumption, investment and public demand bundles. I then define the substitution component of final demand as the residual between $fd_{j,t}$ and $fd^{y}_{j,t}$:

$$fd^{s}_{j,t} = fd_{j,t} - fd^{y}_{j,t} \tag{C.3}$$

Finally, I allocate intermediate inputs into production to the final demand and intermediate input components to express value added output as the sum of value-added demand:

$$y^{va}_{j,t} = fd^{y,va}_{j,t} + fd^{s,va}_{j,t} + \sum_{k}^{\mathcal{F}} x^{va}_{k,j,t} \tag{C.4}$$

where:

$$fd^{y,va}_{j,t} = fd^{y}_{j,t} - \frac{fd^{y}_{j,t}}{y_{j,t}} \sum_{k=1}^{\mathcal{F}} x_{j,k,t} \tag{C.5}$$

$$fd^{s,va}_{j,t} = fd^{s}_{j,t} - \frac{fd^{s}_{j,t}}{y_{j,t}} \sum_{k=1}^{\mathcal{F}} x_{j,k,t} \tag{C.6}$$

$$x^{va}_{k,j,t} = x_{k,j,t} - \frac{x_{k,j,t}}{y_{j,t}} \sum_{k=1}^{\mathcal{F}} x_{j,k,t} \tag{C.7}$$

where $y_{j,t} = fd_{j,t} + \sum_{k=1}^{\mathcal{F}} x_{k,j,t}$ is gross output.

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# COVID-19, public procurement regimes and trade policy[1]

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*This paper analyzes a prominent dimension of the initial policy response to the COVID-19 pandemic observed in many countries: the imposition of export restrictions and actions to facilitate imports. Using weekly data on the use of trade policy instruments during the first seven months of the COVID-19 pandemic (January-July, 2020) we assess the relationship between the use of trade policy instruments and attributes of pre-crisis public procurement regulation. Controlling for country size, government effectiveness and economic factors, we find that use of export restrictions targeting medical products is strongly positively correlated with the total number of steps and average time required to complete procurement processes in the pre-crisis period. Membership of trade agreements encompassing public procurement disciplines is associated with actions to facilitate trade in medical products. These findings suggest future empirical assessments of the drivers of trade policy during the pandemic should consider public procurement systems.*

1 We are grateful to Matteo Fiorini, Valeria Perotti and an anonymous referee for helpful comments on a previous draft. This paper draws on an EUI-Global Trade Alert-World Bank project to monitor trade policy measures implemented during the COVID-19 pandemic. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

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## 1. Introduction

One element of the policy response to the COVID-19 pandemic by governments was to greatly expand public procurement (PP) of critical medical supplies, notably personal protective equipment (masks, gloves, face-shields, respirators), ventilators, laboratory equipment (kits, reagents, swabs, laboratory consumables) and medicines. In some countries, this procurement response included requisitioning of available stocks of such products and a ban on their export. Many countries made active use of trade policy instruments to enhance access to essential supplies, involving a mix of measures to facilitate imports (lowering taxes and import tariffs and creating "green channels" at borders to speed through imports) and export controls (Baldwin and Evenett, 2020). WTO rules permit the use of trade restrictions in public emergencies, but require these to be temporary, lasting only for the duration of a crisis. The reason is that use of export controls can give rise to negative spillovers, including by constraining the ability of firms to ramp up production, leading to increased prices, and impeding the ability of other countries to import supplies (Atkinson et al. 2020; Evenett, 2020; Gereffi, 2020; Hoekman et al. 2020).

In most countries, government procurement of goods and services is subject to regulations that seek to ensure 'value for money'. This is reflected in requirements and processes that enhance transparency, assure due process and accountability, and prevent corrupt practices and/or collusion among bidders. A core feature of PP processes is to mimic the market by encouraging (requiring) competition through open calls for tender.[1] International agreements that cover procurement practices – such as the Treaty on the Functioning of the European Union that applies to EU member states, the WTO Agreement on Government Procurement (GPA) and recent vintage preferential trade agreements (PTAs) – embody not only generally accepted good PP practices but require that foreign firms be treated the same as national bidders. The main thrust of such agreements is to open procurement markets to foreign competition.

As do all trade agreements, national procurement regulations and international agreements that discipline PP practices include exceptions that allow governments to respond rapidly to emergencies in ways that may be inconsistent with the rules that apply in normal times. This might take the form of direct contracting for supplies from producers without going through the processes that normally would be used (Baxter and Casady, 2020). At the time of writing it is not yet possible to investigate the extent and effectiveness of emergency procurement measures taken by different jurisdictions.[2] Instead, we examine the relationship between pre-crisis attributes of public procurement regimes as reflected in indicators compiled by the World Bank and the trade policy behavior of countries in the first seven months of the COVID-19 pandemic. Most trade policy activism was observed in the initial months of the pandemic, reflecting the feasibility of applying trade policy instruments very rapidly. Similarly, trade measures can also be removed rapidly—and in principle should be to abide by WTO rules. Global excess demand for protective equipment and COVID-19 medical supplies was met with a massive supply response, attenuating the rationale for using trade policy instruments for an extended period.

We analyze the relationship between PP regimes and trade policy activism during the first seven months of the COVID-19 pandemic using cross-country information on attributes of pre-crisis national public procurement regimes (World Bank, 2020), the coverage of PP in trade agreements (Shingal and Ereshchenko, 2020) and data on changes in trade policy for medical products implemented by governments during January-July 2020 (Evenett et al., 2020). A key feature of the trade policy data is that information is available on a weekly basis, permitting analysis of when trade liberalizing and restrictive policy instruments were imposed and removed.

1 The basic features of good administrative practice in public procurement are summarized in UNCITRAL (2014) and World Bank (2017).

2 Comprehensive and comparable information on whether and how governments diverged from normal practices in procuring supplies does not exist. Cocciolo et al. (2020) and OECD (2020a) discuss procurement challenges and experiences during the first seven months of the COVID-19 pandemic.

Our results suggest that after controlling for country size, government effectiveness, economic factors and the incidence of COVID-19 cases, restrictions on exports of medical products and import liberalization are positively correlated with pre-crisis attributes of PP regimes. The total number of steps, in particular, and average time taken to complete procurement processes are strongly associated with reducing import barriers and imposition of export controls. Membership of trade agreements with public procurement disciplines – both PTAs and the WTO GPA – is associated with greater openness, reflected in actions to facilitate trade in medical products.

The rest of the paper is structured as follows. Section 2 briefly discusses related literature. Section 3 provides an overview of the use of trade policy between January and July 2020. Section 4 presents the empirical methodology. Section 5 discusses the data sources for the explanatory and control variables and provides some descriptive statistics for these variables. Section 6 discusses the estimation results. Section 7 concludes.

**2. Related literature and hypotheses**

We are not aware of studies that analyze the relationship between public procurement and trade policy responses during public health emergencies. The extant studies on public procurement and COVID-19 include a focus on strategies procuring authorities can (should) use to rapidly ramp up purchases of essential products needed by public health authorities and care providers. Procurement of healthcare-related products usually involves a prolonged multi-stage process that takes time. In times of crisis procuring agencies may need to dispense with normal practices to meet urgent needs for critical equipment and supplies (Sanchez-Graells, 2020). This could include responding to firms that make unsolicited proposals (Baxter and Casady, 2020) and partnership-based approaches with the private sector or other governments (Vecchi et al. 2020). In the case of the EU, the European Commission took several measures to facilitate procurement of essential supplies, including through a (voluntary) coordinated joint procurement mechanism (Beuter, 2020; European Commission, 2020). Some governments directly contracted with large producers, bypassing standard competitive procedures stipulated in public procurement regulations (Hoekman et al. 2020). While warranted, there are risks associated with diverging from standard PP practices, including higher cost procurement, greater vulnerability to fraud, and diminished accountability and less transparency in contracting (Atkinson et al. 2020).

Trade can play a pivotal role in emergencies to ensure that much needed medical supplies get to where they are needed (Gereffi, 2020; OECD, 2020b). Instead, what was observed during the COVID-19 outbreak – amidst shortages of medical supplies – was some governments imposing export control measures and requisitioning domestic supplies of essential goods. Such reactions may exacerbate rather than facilitate provision of vital equipment to healthcare workers by increasing prices, market volatility and distorting investment decisions (Fiorini et al. 2020). The associated disruption to crisis health planning in trading partners makes net importers of medical products particularly vulnerable (Baldwin and Evenett, 2020).

The basic premise underlying the analysis that follows is that attributes of public procurement regulation may influence incentives to use trade policy and decisions to requisition existing stocks and prohibit exports in crises. The idea is that specific attributes of procurement regimes may facilitate or constrain the ability of agencies to rapidly procure needed supplies of medical products in an emergency. PP practices that are designed to control corruption, ensure accountability through due process, transparency, nondiscrimination, and competitive bidding may constrain the ability to respond rapidly. Conversely, PP regimes that are efficient in the sense of allocating contracts more rapidly may be more conducive to addressing an emergency and attenuate incentives to resort to trade restrictions. We do not have strong priors on whether the relationship will be positive or negative but treat this as an empirical question.

Several dimensions of PP policy may be salient in influencing the likelihood that trade policy is used. For example, "buy national" prescriptions reflecting industrial development objectives may be

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accompanied by restrictive import policies to support domestic production. In circumstances where domestic production capacity is too small to satisfy a crisis-induced increase in demand, a policy bias towards domestic sourcing may be associated with a temporary reduction of removal of import restrictions. The higher the initial import barriers the greater the scope for liberalization. In short, differences in the attributes of PP regimes may be associated with differences in trade policy responses to a global pandemic.

In our analysis of PP regimes we are limited by the availability of indicators that characterize salient attributes of PP regimes.[3] One relevant feature of procurement systems on which comparable information is reported on a cross-country basis is the average time taken to complete procurement processes. Countries where PP takes more time may be at a disadvantage in procuring supplies even if standard processes are not applied in a crisis. For example, insofar as a nation's PP "type" is common knowledge and suppliers prefer to sell products in short supply to buyers that can credibly offer rapid contracting and processing of payments. Another attribute of prevailing PP regimes is membership of the WTO GPA and PTAs that encompass government procurement. We expect that members of such PP-liberalizing trade agreements will make less use of trade restrictions in a crisis than other countries. To the best of our knowledge these are issues that have not been investigated in the extent literature on procurement and trade, which has focused on home bias in the allocation of public contracts and associated impacts on costs and productivity.[4]

## 3. Trade policy measures during COVID-19

The source of trade policy data used in the analysis is a European University Institute (EUI), Global Trade Alert (GTA) and World Bank project that tracks changes in trade policies for medical products starting on January 1, 2020. The exercise classifies measures as restrictive or liberalizing and differentiates between type of instrument (tariff, quota, licensing requirement, ban, etc.). A unique feature of the project is that it includes information on the date of announcement, implementation, and removal (if applicable) of each reported measure.[5]

As of mid-July 2020, the dataset documented 414 trade policy measures taken by over 100 distinct jurisdictions. The measures include 209 measures liberalizing imports of protective equipment, medical supplies and medicines implemented in 106 jurisdictions and 191 export controls imposed by 91 countries for the same set of products. The most common liberalizing measures were reduction in import tariffs, while export bans were the most common restrictive measure across countries. Data on trade policy measures are available for 133 countries.

We focus on the first seven months of 2020 because this is the period in which most trade policy measures were imposed. Our research question is whether attributes of prevailing PP regimes are associated with the imposition of trade measures. While the supply of essential goods was largely fixed in the initial period of the crisis, over time, as supply responds to increased demand, this will attenuate the perceived need for exports controls and import liberalization, confounding inferences regarding the possible relationship between PP regulation and use of trade policy in the initial period of a public emergency which is what we are interested in. The GTA dataset shows that some governments began to

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3 For example, cross-country data on the extent to which jurisdictions include "buy national" provisions or PP processes include preferences for specific types of domestic bidders, such as SMEs, is not available. See e.g., Hoekman and Tas (2020).

4 See e.g., Shingal (2015), Kutlina-Dimitrova and Lakatos (2016), Hoekman and Sanfilippo (2020).

5 Evenett et al. (2020) provide an overview of the pattern of trade policy activism that emerges from the data. The data can be accessed at: https://www.globaltradealert.org/reports/54. The methodology used to collect and validate the data, as well as a listing of the Harmonized System (HS) codes for the products covered by the exercise can be found at: https://globalgovernanceprogramme.eui.eu/wp-content/uploads/2020/05/Methodologynote050420.pdf

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roll back trade measures starting in June 2020, a pattern that strengthened in the summer and fall of 2020 (see Evenett et al. 2020).[6]

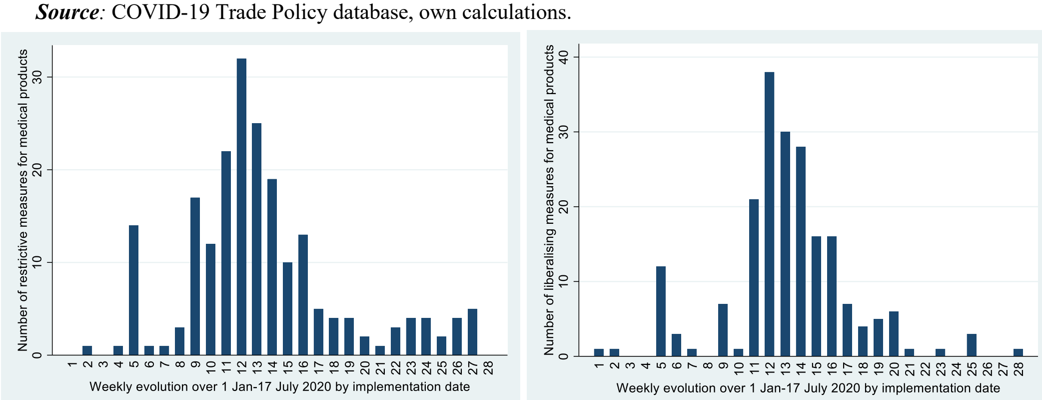
Figure 1 shows the weekly evolution of trade restrictive measures on imports and exports of medical products according to the date of implementation of the measures. The number of restrictive measures on medical products increased exponentially as of the end of March. This coincides with the beginning of the COVID-19 pandemic and the growing demand for medical products worldwide. There were a limited number of liberalizing measures implemented for medical products during the first two months of the year. However, the trend changed drastically as of the end of March, when this number started growing rapidly: the number of such measures more than doubled over a month from 77 measures at the end of March to 174 measures at the end of April. This trend is noteworthy as the period of the spike coincides with the "acknowledged" outbreak of the COVID-19 pandemic and the growing demand for protective equipment and medical products worldwide.

Close to half of all measures were implemented in March 2020. Starting in May there is a gradual decline in the imposition of measures. Based on countries and measures where a removal date is explicitly mentioned in the database, restrictive measures were implemented for a shorter duration (58 days) on average than liberalizing measures (71 days). Within these distributions, the duration of restrictive measures for medical products ranges from as brief as 2 days in the case of an export ban imposed by Slovenia to 137 days for an export ban imposed by Azerbaijan (Figure 2). Similarly, for liberalizing measures the duration ranges from as brief as 11 days in the case of import tariff liberalization by Dominican Republic to 104 days for import tariff liberalization by South Korea.

**Figure 1: Trade measures for medical products (weekly, January-July 2020)**

***Export restrictions*** ***Import liberalization***

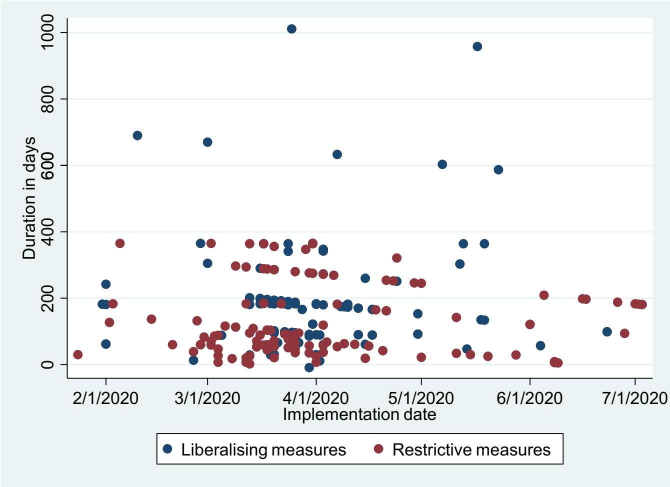
***Source****:* COVID-19 Trade Policy database, own calculations.




***Note:*** The data at the end of each week do not consider the measures that were removed (with a removal date in that week).

[6] The empirical analysis accounts for roll back of measures during the period as we can distinguish between measures that were implemented and subsequently removed and those that remained in force as of July 2020.

**Figure 2. Duration of trade measures for medical products by implementation date**




*Source:* COVID-19 Trade Policy database, own calculations

High and upper middle-income countries, according to the World Bank income classification, enacted more trade policy measures targeting the medical sector than other countries (Evenett et al. 2020). As already mentioned, many of the trade restrictive and liberalizing measures that were adopted to increase the availability of personal protective equipment and medical supplies at the beginning of the COVID-19 pandemic outbreak were subsequently removed. We consider this dynamic in the empirical analysis.

## 4. Empirical methodology

We assess the relationship between different attributes of public procurement regulation and trade policy measures imposed by countries on imports and exports separately by estimating the following equations:[7]

$$Num^{M,T}{}_j = \alpha + \emptyset_k Proc_{kj} + \Sigma\beta_z z_{zj} + \varepsilon_j \quad (1)$$
$$Num^{X,T}{}_j = \alpha + \emptyset_k Proc_{kj} + \Sigma\beta_z z_{zj} + \varepsilon_j \quad (2)$$

where $Num^{M,T}{}_j$ is the number of import ("*M*") policy measures imposed by type ("*T*" = liberalizing, restrictive) in implementing jurisdiction j; $Num^{X,T}{}_j$ is the number of export ("*X*") policy measures imposed by type ("*T*" = liberalizing, restrictive) in implementing jurisdiction *j*; $Proc_{kj}$ is the vector of public procurement variables for country *j*; $z_{zj}$ is a vector of country- and country-sector specific control variables; $\alpha$ is the constant term and $\varepsilon_j$ is the error term. Equations (1) and (2) are estimated separately for liberalizing and restrictive measures imposed on medical products and personal protective equipment.

7 We organize the data as a cross-section instead of a panel because the dependent variable is available by country on a weekly basis but all explanatory variables, except those on the incidence of COVID-19, are only available for each country annually in the year 2018 or before. The annual variation in our variables of interest will thus not explain the weekly or monthly variation in the count of trade policy measures imposed during the pandemic. This said, we account for the time dimension of the trade policy measures by computing the duration of the measures (where a removal date is reported in the GTA dataset) and replacing the dependent count variables in equations (1) and (2) with their respective duration. Results are reported in Table 4.

The procurement vector comprises variables reflecting the timeliness ($Total\_time_j$), administrative procedures ($Total\_steps_j$), efforts to lower transactions costs ($Eproc_j$) and commitments to open government procurement regimes to foreign competition. The first two variables denote the pre-crisis average total time and number of steps to complete procurement processes in each country or jurisdiction. Use of e-procurement is measured as the share of e-procurement in total procurement, based on the range categorization reported in the World Bank Doing Business Contracting with the Government indicator: less than 25%, 25%-50%, 50%-75% and 100%. Greater reliance on e-procurement may have a positive or negative association with resort to trade measures. It may facilitate a rapid response by making it easier for small and medium-sized enterprises (SMEs) – which account for a large share of the total number of firms in any economy – to sell essential supplies to the authorities (SMEs that do not already participate in PP may be able to retool relatively quickly if it is clear there is demand for their output). But this may also go the other way if the fixed costs associated with registration, certification and approval of new firms to bid to provide medical supplies are significant and take time to complete.

Openness of procurement regimes is proxied by a binary variable indicating GPA membership ($GPA_j$) and by the number of deep procurement agreements (DPAs) signed by each country with trading partners ($Num\_DPA_j$). Membership of the GPA and the number of DPAs signed by a country implies more open PP regimes, which may be associated with a lower likelihood of imposing trade-restrictive measures. Conversely, transparency, due process and nondiscrimination commitments made in these agreements may impede rapid responses in procurement and induce governments to resort to export controls in the initial phase of the crisis.

The control vector includes country size, the log of population ($POP_j$); a measure of geographic distance to global markets, the log of market penetration ($MP_j$), computed as a distance ($d_{ij}$) weighted measure of other countries' GDP ($GDP_i$), i.e. $MP_j = \Sigma_i(GDP_i/d_{ij})$; and a measure of government effectiveness ($GE_j$). Both equations also include (i) the share of imports of medical goods in country *j*'s total imports ($Msh_j$); (ii) country *j*'s standardized revealed comparative advantage index ($RCA_j$) for medical goods;[8] and (iii) the (log of) simple average applied tariff rate [$ln(1+Tar_j)$] in country *j* on medical goods.

Large, populous countries are likely to have market power, which in turn may induce governments to use trade policy to affect their terms of trade. Government effectiveness is directly correlated with per capita income. A more effective government is more likely to adapt procurement processes to source needed medical supplies, thereby reducing the incentive to change trade policy. The import share, RCA and import tariff variables proxy for political economy forces that shape pre-crisis trade policy and can be expected to influence the duration of crisis trade measures.[9] Higher import dependence is suggestive of a pro-liberalization domestic political economy. Conversely, high levels of import restrictions suggest a country has industrial development goals. Such countries may relax import barriers temporarily to improve access to essential commodities but are more likely to reimpose import barriers more rapidly to support local production, reflecting prevailing industrial policy objectives. An RCA > 1 for exports of medical products implies supply-side capacity that may induce governments to remove export controls more rapidly if a decision is taken to temporarily restrict exports in response to the pandemic spike in demand.

We also control for the number of COVID-19 cases ($Covid\_cases_j$) and the number of related deaths ($Covid\_deaths_j$) as of 22 July 2020. We do this because the number of cases and deaths may affect the likelihood of removing (retaining) trade policy instruments, with greater case numbers potentially

8 The RCA is defined as the ratio of country *j* exports of product *i* to its total exports of all products divided by the same ratio for the world. If the $RCA_{ji} > 1$ a country is said to have a revealed comparative advantage in *i*.

9 Leibovici and Santacreu (2020) analyze the potential role of net importer and net exporter status as a potential driver of trade policy activism in a pandemic.

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associated with more export restrictions, keeping them on longer and/or deeper liberalization of imports of essential supplies. We do not use number of cases/deaths for the early months of the pandemic because in most countries case numbers and deaths were low in the initial period – February-March – when most of trade measures were put in place by those countries that decided to do so.

The dependent variable in all equations is characterized by over-dispersion, which biases log linear OLS estimation. Given the scale-dependence of the negative binomial pseudo-maximum likelihood estimator, we estimate the equations using the Poisson- pseudo-maximum likelihood estimator (PPML) (Santos Silva and Tenreyro, 2006). Given that our interest is in trade policy measures imposed in response to COVID-19 in the first half of 2020 and all the explanatory variables pertain to 2017-2018 (see Section 5 below), endogeneity emanating from reverse causality is unlikely to be a concern in estimating equations (1) and (2). There could however be omitted variable biases, especially given that we cannot include any fixed effects. We therefore refrain from drawing any inferences about causality in the presentation of our results.

## 5. Data sources and descriptive statistics

The procurement variables used as explanatory variables in the empirical analysis are sourced from the World Bank Doing Business Contracting with the Government indicator and pertain to the year 2018. Data are available for all 133 jurisdictions reported to have used trade measures in the first half of 2020 in the GTA trade policy dataset (Appendix Table 1).[10]

PP processes in richer countries tend to require both a smaller number of steps and less time for completion on average (Figure 3, bottom panels). The total number of steps range from a low of 12 (Singapore) to a high of 21 (Honduras, Hungary, Iran, Laos, Myanmar and Oman). The average time taken to complete a procurement process ranges from 270 (South Korea) to 2062 (Venezuela) days. The sample mean is 18 steps and 717 days, respectively. Richer countries also tend to use e-procurement more on average (Figure 3, top right panel). The share of e-procurement in total procurement ranges from less than 25% for most African countries to more than 75% for EU and ASEAN Member States.

$GPA_j$ is constructed using information on membership of the WTO's Agreement on Government Procurement as of July 2020; and $Num\_DPA_j$ is constructed using data from Shingal and Ereshchenko (2020), which cover all PTAs in effect until March 2017.[11] On average richer countries tend to be members of more DPAs (Figure 3, top left panel). The number of non-zero DPAs ranges from 1 for West Asian countries to 26 for the EU. There are 32 WTO GPA members in the sample, mostly comprising high-income countries.

The control variables are sourced as follows: population and GDP data are from the World Bank World Development Indicators; market penetration ($MP_j$) is computed using bilateral distance data from CEPII (Head et al. 2010); and government effectiveness ($GE_j$) is sourced from the Worldwide Governance Indicators (Kaufmann et al. 2011). Trade data to construct the import share and RCA variables are from UN Comtrade. Import tariffs are from UNCTAD TRAINS/WITS. Data on COVID-19 cases are from the WHO (https://covid19.who.int/table). Appendix Table 2 reports summary statistics for all variables used in the analysis. Apart from COVID-19 cases and deaths that pertain to the third week of July 2020, all control variables are the average for the years 2017 and 2018.

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10 Jurisdictions imposing measures include the Eurasian Economic Union, the EU, and the South African Customs Union (SACU). Measures imposed by these blocs are allocated to their member states for the purpose of analysis.

11 Shingal and Ereshchenko (2020) measure the "depth" of procurement provisions in PTAs on the basis of seven broad attributes: non-discrimination; coverage in terms of goods, services (including construction) and type of procuring entity (central, sub-central government and utilities); procedural disciplines; ex-ante and ex-post transparency, dispute settlement; and new issues (e-procurement, sustainable procurement, SME participation, adoption of safety standards, and cooperation on matters of public procurement).

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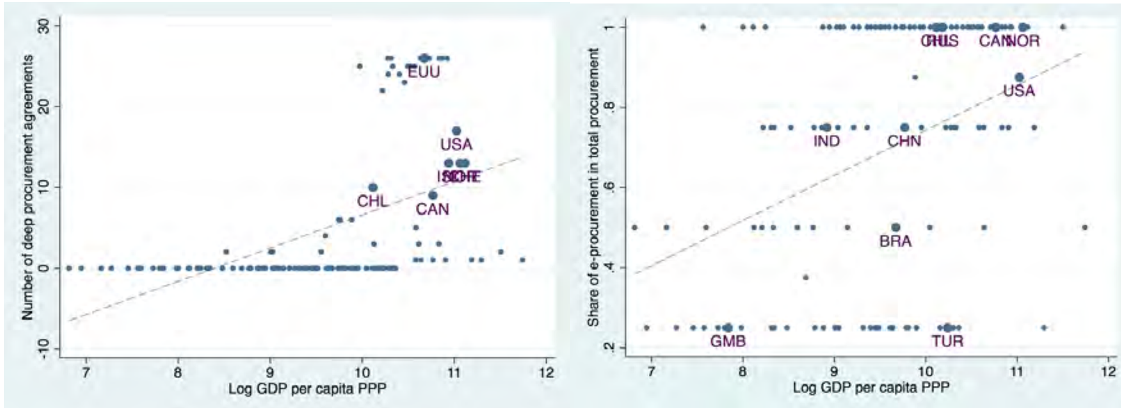
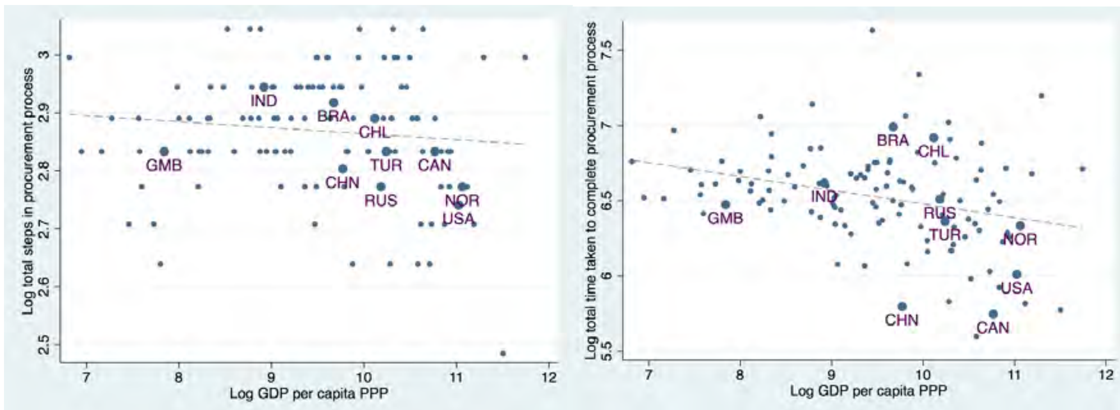
**Figure 3: Scatterplots of procurement variables against per capita income**




*Source:* Shingal and Ereshchenko (2020), World Bank WDI

*Source:* World Bank, Doing Business and WDI




*Source:* World Bank, Doing Business and WD

## 6. Results

Table 1 reports the results from PPML estimation of equations (1) and (2) separately for liberalizing and restrictive measures imposed on medical goods, with standard errors clustered by country in each case. Results reported in Table 2 replicate the analysis in Table 1 but distinguish between measures that were imposed and subsequently removed within the sample period and those that remained in effect as of mid-July 2020. Table 3 reports the results from the PPML estimation of equations (1) and (2) applied to specific types of trade measures, i.e., restriction or liberalization of exports or imports, respectively. Finally, based on the dates of implementation and removal, Table 4 reports the results from estimating equations (1) and (2) using as dependent variable the duration of the respective measure and not the total number of measures.

The average number of pre-crisis steps required to complete procurement processes is found to be positively correlated with the number of trade liberalizing measures, on both the import and export side. This result reflects measures that were still in force at the end of the sample period (see Table 2, columns 1 and 3). In contrast, this variable is positively correlated with the duration of import restrictive measures (Table 4, column 2).[12] There is also a relatively strong correlation between the total time taken for procurement and the number of trade restrictions, on both the import and export side. This result reflects measures that were still in force at the end of the sample period (see Table 2, columns 2 and 4). On the import side this result is driven by import tariff levels, while on the export side it reflects licensing requirements (Table 3, column 4 and 6). In contrast, the duration of import restrictions is found to be inversely related to pre-crisis average time to complete procurement processes (Table 4, column 2). Thus, both attributes of pre-crisis PP regimes are strongly correlated with trade policy activism during the initial months of the pandemic, which supports the contention that jurisdictions with PP systems characterized by more steps or stages and processes that take longer on average to complete made greater use of trade policy to increase domestic availability of protective equipment and medical supplies.

This is not the case for e-procurement. Greater use of e-procurement is only weakly associated with the number of export restrictions (Table 1), although the association is stronger for use of export bans (Table 3). In contrast, e-procurement is found to be inversely related to import restrictions that were imposed but subsequently removed (Table 2, column 6) as well as the duration of such measures (Table 4, column 2).

Turning to our international procurement policy variables, membership of the GPA is positively associated with the number of liberalizing measures for imports of medical products as well as removal of export restrictions (Table 1). The former result is also found when attention is restricted to measures that are still in force at the end of the sample period (Table 2). These findings provide some support for a presumption that members of the GPA are more inclined (committed) to maintaining open markets. At the more disaggregated trade instrument level we find a weakly positive association between GPA membership and the use of export bans, a finding that attains strong statistical significance when focusing on the duration of export restrictions: GPA membership is positively correlated with maintaining export controls during the whole period under analysis if a member decides to use this instrument (Table 4).

The greater the number of DPAs a jurisdiction has signed, the smaller is the number of import restrictive measures imposed on medical products – the coefficient on $Num\_DPA_j$ is negative and statistically significant at conventional levels. This result seems to be driven by measures that were still in effect at the end of our sample period (see Table 2, columns 1-2). The analysis focusing on

[12] The relatively small number of instances in which jurisdictions are observed to (re-)impose import barriers during the sample period lead to a fully saturated model when we analyze this specific type of trade measure. The results in Table 2, column (6) and Table 4, column (2) for (re-)imposition of import restrictions therefore need to be interpreted with caution.

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disaggregated measures reveals this is driven mainly by import tariffs (Table 3, columns 1 and 4). These results suggest that countries with more DPAs are more open, liberalizing imports and less prone to (re-)impose import barriers.

Among the control variables, country size is positively correlated, significant at the 1% level, with the number of export restrictions on medical products (Table 1). The same result is obtained for the measure of distance to markets – greater distance from markets is associated with greater use of export restrictions. These findings seem to be driven by measures that were still in effect at the end of the sample period (i.e. that were not removed within the seven-month period under consideration) (Table 2). Indeed, conditional on measures not having been removed during the period there is some suggestion that larger countries may also pursue import liberalization, i.e., to operate on both margins, presumably with the aim to expand domestic availability of medical products. This finding is consistent with terms-of-trade models of trade policy.

**Table 1: Number of export and import measures targeting medical products**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **lib_m** | **res_m** | **lib_x** | **res_x** |
| Ln(Total_steps$_j$) | 2.20** | 6.28** | 2.89** | 1.35 |
| | (1.08) | (3.02) | (1.47) | (1.22) |
| Ln(Total_time$_j$) | 0.39 | 1.34 | -0.60 | 1.72** |
| | (0.31) | (0.91) | (0.76) | (0.71) |
| Eproc$_j$ | 0.03 | -0.84* | 0.47 | 0.30* |
| | (0.11) | (0.46) | (0.34) | (0.18) |
| Ln(Num_DPA$_j$) | -0.31** | -1.97*** | | -0.04 |
| | (0.15) | (0.63) | | (0.16) |
| GPA$_j$ | 0.72** | 0.56 | 2.68*** | 0.67* |
| | (0.33) | (0.79) | (0.85) | (0.38) |
| Ln(POP$_j$) | 0.09 | 0.16 | 0.08 | 0.40*** |
| | (0.07) | (0.17) | (0.17) | (0.13) |
| Ln(MP$_j$) | -0.08 | 0.38 | -0.24** | 0.23** |
| | (0.07) | (0.27) | (0.11) | (0.12) |
| GE$_j$ | 0.34* | 2.06** | -0.62 | 0.75** |
| | (0.18) | (0.87) | (0.38) | (0.35) |
| Msh$_j$ | 1.76 | 3.91 | 7.32 | -4.03 |
| | (3.34) | (11.62) | (10.88) | (5.97) |
| RCA$_j$ | 0.18 | 1.50*** | 1.72** | -0.07 |
| | (0.23) | (0.56) | (0.82) | (0.53) |
| Ln(1+Tar$_j$) | 0.44** | 0.23 | 0.44 | -0.46 |
| | (0.22) | (0.48) | (0.46) | (0.32) |
| Ln(Covid_cases$_j$) | 0.05 | 0.37* | -0.49 | -0.09 |
| | (0.10) | (0.21) | (0.32) | (0.17) |
| Ln(Covid_deaths$_j$) | 0.12 | 0.06 | 0.32 | 0.06 |
| | (0.10) | (0.23) | (0.29) | (0.14) |
| Constant | -10.15** | -32.18*** | -6.67 | -16.60*** |
| | (3.98) | (7.22) | (9.12) | (6.25) |
| Observations | 108 | 108 | 108 | 108 |
| R-squared | 0.54 | 0.84 | 0.65 | 0.45 |

***Note*:** Robust standard errors, clustered by country, in parentheses. Levels of significance: *10%, **5%, ***1%.

***Legend*:** lib=liberalizing; m=import policy; res=restrictive; x=export policy; GE: government effectiveness; DPA: deep procurement agreement; GPA: WTO Government Procurement Agreement; RCA: revealed comparative advantage; Msh: import share; Tar: import tariff; POP: population; MP: measure of geographic distance to global markets.

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**Table 2: Number of trade measures by status of implementation**

| | *Measures still in effect as of mid-July 2020* | | | | *Measures no longer in effect as of mid-July 2020* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Variables** | **lib_m** | **res_m** | **lib_x** | **res_x** | **lib_m** | **res_m** | **lib_x** | **res_x** |
| Ln(Total_steps$_j$) | 3.86*** | 3.72 | 20.61*** | 2.75* | -0.12 | 274.81*** | 2.06 | -1.52 |
| | (1.31) | (4.45) | (6.56) | (1.60) | (3.11) | (3.72) | (2.33) | (1.88) |
| Ln(Total_time$_j$) | 0.31 | 1.71* | -13.33*** | 2.04*** | 1.57 | -47.89*** | 0.73 | 1.10 |
| | (0.32) | (1.04) | (3.24) | (0.79) | (2.05) | (1.37) | (1.56) | (0.75) |
| Eproc$_j$ | -0.06 | -1.02** | -0.18 | 0.31 | 0.19 | -0.61*** | 1.06*** | 0.08 |
| | (0.10) | (0.49) | (0.25) | (0.23) | (0.26) | (0.10) | (0.30) | (0.17) |
| Ln(Num_DPA$_j$) | -0.51*** | -2.50*** | 4.35*** | -0.06 | -0.16 | | | 0.11 |
| | (0.15) | (0.71) | (1.35) | (0.20) | (0.25) | | | (0.21) |
| GPA$_j$ | 1.14*** | 1.16 | | 0.71 | 0.09 | | | 0.75* |
| | (0.32) | (1.10) | | (0.53) | (0.63) | | | (0.44) |
| Ln(POP$_j$) | 0.13* | 0.22 | 0.26 | 0.40** | -0.19 | -0.20 | -0.29 | 0.16 |
| | (0.07) | (0.24) | (0.19) | (0.16) | (0.16) | (0.16) | (0.25) | (0.15) |
| Ln(MP$_j$) | -0.13* | 0.25 | -0.11 | 0.31** | 0.21 | 11.23*** | -0.21 | 0.16 |
| | (0.07) | (0.33) | (0.39) | (0.13) | (0.24) | (0.18) | (0.27) | (0.11) |
| GE$_j$ | 0.35** | 3.20*** | -3.03*** | 1.08*** | 0.63 | 8.37*** | -0.31 | 0.21 |
| | (0.16) | (0.52) | (0.97) | (0.38) | (0.54) | (0.67) | (0.83) | (0.43) |
| Msh$_j$ | 4.72 | -5.45 | | | -0.77 | -299.18*** | | |
| | (3.37) | (13.71) | | | (10.44) | (8.57) | | |
| RCA$_j$ | | | -0.75 | -0.26 | | | 1.01* | -0.28 |
| | | | (0.87) | (0.63) | | | (0.61) | (0.44) |
| Ln(1+Tar$_j$) | 0.31 | 0.03 | 2.25** | -0.22 | 1.10** | 29.81*** | -1.61** | -0.42 |
| | (0.21) | (0.41) | (0.93) | (0.29) | (0.52) | (0.54) | (0.67) | (0.40) |
| Ln(Covid_cases$_j$) | -0.03 | 0.15 | -0.34 | 0.01 | 0.10 | 8.20*** | -1.48*** | 0.08 |
| | (0.12) | (0.23) | (0.24) | (0.17) | (0.31) | (0.29) | (0.46) | (0.26) |
| Ln(Covid_deaths$_j$) | 0.20 | 0.47 | -0.52 | 0.01 | 0.04 | -7.06*** | 1.20*** | -0.15 |
| | (0.13) | (0.32) | (0.35) | (0.15) | (0.26) | (0.23) | (0.34) | (0.20) |
| Constant | -13.92*** | -26.98*** | 20.79* | -24.84*** | -14.54 | -642.77*** | -5.16 | -3.85 |
| | (4.09) | (9.28) | (11.41) | (7.86) | (9.93) | (8.66) | (13.02) | (6.68) |
| Observations | 97 | 97 | 75 | 97 | 50 | 33 | 43 | 50 |
| R-squared | 0.66 | 0.86 | 0.35 | 0.45 | 0.30 | 1.00 | 0.63 | 0.48 |

***Note***: Robust standard errors, clustered by country, included in parentheses. Levels of significance: *10%, **5%, ***1%.

**Table 3: Types of trade measures used (number)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Variables** | **m_lib_t** | **m_lib_tx** | **m_lib_oth** | **m_res_t** | **x_res_b** | **x_res_lic** | **x_res_oth** |
| Ln(Total_steps$_j$) | -0.02 | 0.24 | 1.49* | 2.36*** | 1.63** | 2.38** | -0.39 |
| | (0.43) | (0.62) | (0.81) | (0.86) | (0.79) | (0.99) | (0.91) |
| Ln(Total_time$_j$) | 1.23 | 3.38** | 2.29 | 7.86*** | -1.45 | 5.37*** | -0.48 |
| | (1.35) | (1.62) | (3.40) | (2.66) | (1.57) | (1.66) | (2.19) |
| Eproc$_j$ | 0.03 | 0.01 | 0.01 | -0.30 | 0.39** | 0.44 | -0.59 |
| | (0.15) | (0.17) | (0.22) | (0.28) | (0.17) | (0.36) | (0.38) |
| Ln(Num_DPA$_j$) | -0.42** | 0.17 | -0.50 | -1.69*** | -0.04 | -0.11 | 0.67** |
| | (0.18) | (0.26) | (0.34) | (0.42) | (0.19) | (0.25) | (0.32) |
| GPA$_j$ | 0.72* | 0.86 | 0.36 | 0.30 | 0.66* | 0.89 | 0.95 |
| | (0.41) | (0.54) | (0.63) | (0.72) | (0.35) | (0.69) | (0.99) |
| Ln(POP$_j$) | 0.05 | 0.00 | 0.18 | 0.41* | 0.29* | 0.55*** | 0.33 |
| | (0.10) | (0.12) | (0.18) | (0.23) | (0.16) | (0.17) | (0.27) |
| Ln(MP$_j$) | -0.09 | -0.08 | 0.07 | 0.38 | 0.26** | 0.25* | -0.23* |
| | (0.09) | (0.08) | (0.20) | (0.24) | (0.12) | (0.15) | (0.13) |
| GE$_j$ | 0.25 | 0.03 | 0.65 | 0.84 | 0.33 | 1.29*** | 0.46 |
| | (0.23) | (0.28) | (0.48) | (0.68) | (0.40) | (0.46) | (0.64) |
| Msh$_j$ | 4.21 | -2.14 | 1.33 | 9.77 | -4.49 | -3.82 | 4.35 |
| | (3.90) | (5.69) | (8.99) | (11.11) | (6.88) | (10.05) | (8.17) |
| RCA$_j$ | -0.05 | 0.35 | 0.73 | 1.42*** | 0.12 | -0.07 | 0.29 |
| | (0.28) | (0.38) | (0.51) | (0.49) | (0.56) | (0.61) | (0.89) |
| Ln(1+Tar$_j$) | 0.37 | 0.86** | 0.43 | -1.44*** | -0.27 | -0.82 | 1.25** |
| | (0.30) | (0.42) | (0.39) | (0.40) | (0.34) | (0.54) | (0.63) |
| Ln(Covid_cases$_j$) | 0.14 | -0.09 | -0.03 | 0.37 | -0.12 | -0.07 | 0.59* |
| | (0.13) | (0.18) | (0.29) | (0.30) | (0.20) | (0.22) | (0.35) |
| Ln(Covid_deaths$_j$) | 0.12 | 0.21 | -0.01 | 0.28 | 0.13 | -0.00 | -0.55** |
| | (0.13) | (0.16) | (0.22) | (0.27) | (0.16) | (0.19) | (0.24) |
| Constant | -6.14 | -13.91** | -18.48* | -45.21*** | -9.11 | -33.88*** | -2.61 |
| | (4.84) | (6.98) | (10.91) | (7.92) | (7.49) | (10.93) | (9.31) |
| Observations | 108 | 108 | 108 | 108 | 108 | 108 | 108 |
| R-squared | 0.51 | 0.29 | 0.17 | 0.91 | 0.28 | 0.56 | 0.29 |

***Note***: Robust standard errors, clustered by country, included in parentheses. Levels of significance: *10%, **5%, ***1%.

***Legend***: lib=liberalizing; m=import policy; res=restrictive; x=export policy; t=tariff; tx=tax; oth=other; b=ban; lic=licensing requirement

This "aggregate" finding across the four main categories of trade policy actions is unpacked in Table 3, which reports results for seven different types of instruments that are most frequently observed in the GTA dataset. This more disaggregated focus reveals large countries focused more on import tariffs as well as export bans and export licensing requirements.[13] Distance to markets is positively associated with restrictive export measures and inversely correlated with liberalizing export measures on medical products; the former finding driven by measures still in force (see Table 2, column 4). Conversely, if the focus is on measures that were removed during the period, this variable is strongly correlated with re-imposition of import restrictions, with a coefficient estimate that is statistically significant at the 1% level (Table 2, column 6). Distance has a very similar pattern as country size does on the export side (Table 3).

**Table 4: Correlates with the duration of aggregate measures**

| **Variables** | (1) **lib_m** | (2) **res_m** | (3) **res_x** |
|---|---|---|---|
| $Ln(Total\_steps_j)$ | 2.98 | 385.15*** | -1.33 |
| | (2.80) | (4.08) | (1.84) |
| $Ln(Total\_time_j)$ | 0.50 | -49.43*** | -0.47 |
| | (1.34) | (2.29) | (0.69) |
| $Eproc_j$ | -0.33 | -1.77*** | -0.29 |
| | (0.35) | (0.13) | (0.20) |
| $Ln(Num\_DPA_j)$ | 0.11 | | -0.11 |
| | (0.33) | | (0.18) |
| $GPA_j$ | 1.27 | | 1.37*** |
| | (0.85) | | (0.51) |
| $Ln(POP_j)$ | 0.14 | 3.77*** | -0.20 |
| | (0.22) | (0.20) | (0.13) |
| $Ln(MP_j)$ | 0.07 | 15.76*** | -0.09 |
| | (0.23) | (0.27) | (0.10) |
| $GE_j$ | 1.11** | 10.06*** | -0.29 |
| | (0.50) | (0.89) | (0.36) |
| $Msh_j$ | -11.95 | -238.30*** | -18.44** |
| | (14.68) | (10.82) | (9.18) |
| $RCA_j$ | -2.43** | 0.32 | 0.04 |
| | (1.01) | (0.47) | (0.55) |
| $Ln(1+Tar_j)$ | 1.04** | 38.76*** | -0.13 |
| | (0.49) | (0.69) | (0.33) |
| $Ln(Covid\_cases_j)$ | -0.11 | | 0.42 |
| | (0.40) | | (0.27) |
| $Ln(Covid\_deaths_j)$ | 0.14 | -2.06*** | -0.22 |
| | (0.31) | (0.16) | (0.25) |
| Constant | -10.91 | -955.74*** | 10.36** |
| | (7.52) | (9.43) | (4.28) |
| Observations | 50 | 33 | 50 |
| R-squared | 0.20 | 1.00 | 0.31 |

***Note:*** Robust standard errors, clustered by country, in parentheses. Levels of significance: *10%, **5%, ***1%.

[13] A possible rationale for (re-)imposing import tariffs is to protect domestic producers of medical inputs and products.

Government effectiveness is positively correlated with all categories of trade policy measures, especially export licensing requirements (Table 3), except for imposition of import barriers, especially when it comes to measures still in force at the end of the sample period (Table 2). Higher initial tariffs are positively correlated with liberalization of imports (Table 1), which is expected as the higher the pre-crisis tariffs the greater the expected impact of removal of the tax on prices (or more realistically, attenuation of price rises for essential products). The result seems driven by liberalization of domestic taxation on imported medical products (Table 3). Conversely, when it comes to measures that are removed during the sample period, pre-crisis tariffs are strongly associated with re-imposition of import barriers – which may reflect a return to the initial level of protection for the products concerned (Table 2, column 6). This can also be inferred from the large positive correlation between pre-crisis tariff levels and the duration of import policy measures imposed on medical products (Table 4).

Supply-side capacity (proxied by a revealed comparative advantage in exporting medical products) is positively correlated with both import restrictive and export liberalizing measures (Table 1). Conversely, greater reliance on imports of medical products is not correlated with the number of import or export measures imposed on medical products, in either aggregate or disaggregated analysis, which is a counter-intuitive result (Table 1). However, import reliance is strongly negatively associated with re-imposition of import barriers (Table 2), consistent with higher import dependence disincentivizing imposition of import barriers.[14] This variable is also found to be negatively correlated with the duration of restrictive measures imposed (Table 4, columns 2-3).

## 7. Conclusion

Controlling for country size, government effectiveness and economic factors that may influence trade policy, we find evidence that the use trade measures targeting medical products in the first seven months of the global COVID-19 pandemic is positively correlated with pre-crisis attributes of national public procurement regimes. Jurisdictions with PP systems that are characterized by more steps or stages and processes that take longer on average to complete made greater use of trade policy to increase domestic availability of protective equipment and medical supplies. At the same time, we find that GPA membership and participation in DPAs is associated with maintaining more open markets for medical products. Jurisdictions that have signed agreements that require nondiscrimination between foreign and domestic firms do more to reduce import barriers and are slower to reimpose import restrictions.

While striking and novel, our results are no more than suggestive. They call for more in-depth analysis that includes information on what was done by different jurisdictions to procure medical products and protective equipment on an emergency basis, and the global supply response by business producing the relevant products. The main conclusion we draw from our analysis is that future research assessing policy responses to the COVID-19 pandemic should consider both the efficacy and efficiency of public procurement processes and the recourse made to trade policy in efforts by governments to address the sharp rise in domestic demand for personal protective equipment and medical supplies.

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[14] This will depend on government objectives and domestic political economy forces – a subject that is beyond the scope of the present analysis.

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**Appendix Table 1: Jurisdictions included in the sample**

Albania, Algeria, Angola, Anguilla, Antigua & Barbuda, Argentina, Armenia, Australia, Azerbaijan, Bahamas, Bahrain, Bangladesh, Belarus, Belgium, Belize, Bermuda, Bhutan, Bolivia, Botswana, Brazil, Brunei, Darussalam, Bulgaria, Burkina Faso, Cambodia, Cameroon, Canada, Chad, Chile, China, Colombia, Costa Rica, Cyprus, Czech Republic, Côte d'Ivoire, DR Congo, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Eurasian Economic Union, European Union, Fiji, France, Gambia, Georgia, Germany, Greece, Guatemala, Guinea, Guyana, Honduras, Hungary, Iceland, India, Indonesia, Iran, Israel, Italy, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Libya, Malawi, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Moldova, Montserrat, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Caledonia, New Zealand, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Qatar, South Korea, Sudan, Romania, Russian Federation, Samoa, Saudi Arabia, Senegal, Serbia, Seychelles, Singapore, Slovakia, Slovenia, South Africa, Southern African Customs Union, Sri Lanka, St. Kitts and Nevis, St. Vincent and the Grenadines, Suriname, Switzerland, Syria, Taiwan, Tajikistan, Thailand, Togo, Turkey, Turks & Caicos Islands, Uganda, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, Zambia, and Zimbabwe.

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**Appendix Table 2: Summary statistics**

| Variable name | Variable description | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| ***Dependent variable*** | | | | | | |
| lib_m | Count of import liberalizing measures on medical products | 133 | 1.91 | 2.68 | 0 | 22 |
| res_m | Count of import restrictive measures on medical products | 133 | 0.24 | 1.12 | 0 | 10 |
| lib_x | Count of export liberalizing measures on medical products | 133 | 0.16 | 0.37 | 0 | 1 |
| res_x | Count of export restrictive measures on medical products | 133 | 1.49 | 2.98 | 0 | 30 |
| ***Control variables*** | | | | | | |
| pop | Population (mln) | 128 | 57 | 179 | 0.04 | 1390 |
| ge | Government effectiveness | 127 | 0.06 | 0.88 | -1.81 | 2.23 |
| mp | Market penetration (USD mln) | 130 | 168 | 481 | 0 | 5200 |
| Msh | Share of medical imports in total imports | 129 | 0.06 | 0.03 | 0.01 | 0.17 |
| RCA | Standard RCA for medical products | 129 | -0.47 | 0.44 | -0.99 | 0.58 |
| Tar | Simple average applied tariff rate on medical products | 119 | 5.93 | 4.57 | 0 | 27.59 |
| COVID_cases | Cumulative count of COVID-19 cases | 130 | 107070 | 400949.8 | 3 | 3805524 |
| COVID_deaths | Cumulative count of deaths due to COVID-19 | 130 | 4294 | 15539.5 | 0 | 140437 |
| ***Procurement variables*** | | | | | | |
| tot_steps | Total steps required to complete procurement process | 122 | 17.72 | 1.76 | 12 | 21 |
| tot_time | Total time to complete procurement process (# of days) | 122 | 716.61 | 245.10 | 270 | 2062 |
| eproc | Share of e-procurement in total procurement | 124 | 0.69 | 0.32 | 0.25 | 1 |
| gpa | Membership of WTO's GPA | 133 | 0.24 | 0.43 | 0 | 1 |
| num_dpa | Number of deep procurement agreements | 133 | 4.36 | 8.71 | 0 | 26 |

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# Industrialization under medieval conditions? Global development after COVID-19[1]

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*Industrialization is vital for inclusive and sustainable global development. The two engines of industrialization – innovation and trade – are in danger of being compromised by the COVID-19 pandemic, under conditions increasingly reminiscent of the medieval world. It comes at a time when innovation had already been stagnating under guild-like corporate concentration and dominance, and the multilateral trade system had been buckling under pressure from a return to mercantilist ideas. The COVID-19 pandemic may cause a permanent reduction in innovation and entrepreneurship and may even bring the 4th Industrial Revolution (4IR) to a premature end. Hence the post-COVID-19 world may be left with trade as the only engine for industrialization for the foreseeable future. If the global community fails to fix the multilateral trade system, the world may start to resemble the Middle Ages in other, even worse, aspects.*

1 An earlier version of this paper was given as a keynote to the Official Launch of the Friends of Industry and Innovation, Geneva, 9 October 2020. I am grateful to the participants for their insightful comments and questions, as well as to Nobuya Haraguchi and Frank Piller for useful feedback. The usual disclaimer applies.

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# 1 Introduction

Industrialization has, most spectacularly since the late 18th century, driven global development. The manufacturing and trade of goods, using increasingly sophisticated technology and labor, have resulted in considerable gains in productivity, consumption, incomes, and general welfare, and remains essential for development (Naudé & Szirmai, 2012; Haraguchi et al., 2017). The rise of manufacturing has been due to the interdependent effects of innovation and trade. Innovation brought new production methods into being, while trade opened up broader markets, allowed specialization and scale economies, and incentivized and spread innovation (Grossman & Helpman, 2015; Thierer, 2016). In short, trade and innovation have been the two engines of industrialization over the past three centuries.

The COVID-19 pandemic, which broke out at the end of 2019, created severe health and economic crises. For instance, the pandemic resulted in more than a million confirmed deaths by October 2020. It places the pandemic amongst the top 6 pandemics since the 14th century (Jorda et al., 2020). As an economic crisis, COVID-19 is amongst the worst since the Second World War, with global GDP likely to shrink at least by 6,2 percent in 2020 (World Bank, 2020). The repercussions of these health and economic crises on industrialization could be substantial. If we want to understand how the COVID-19 pandemic will affect industrialization, and if we want to know how best policymakers should adjust their industrial policies after the pandemic, we need to know how the pandemic will impact on innovation and trade, its two engines.

Impacts will play out over both the short and the long-term. Six months into the pandemic, it is clear that the short-term effects were, as was expected, dramatically negative. It is evident in a sharp decline in new business startups, an increase in actual and expected firm failures (Bartik et al., 2020; Bosio et al., 2020; Fairlie, 2020), and a steep decline in trade (CCSA, 2020). If it was only a once-off, transient shock, one would expect the world to return to pre-2020 trends soon and move on, with a resumption of pre-COVID-19 industrial policies. However, if the COVID-19 shock is longer-lasting, or will have more long-term, persistent consequences, such impacts will have more severe implications for industrialization. The questions therefore are, what are the likely long-term, lasting impacts of the crisis, and how can these be mitigated?

In the remainder of this paper, an attempt to give a preliminary answer to these will be made. In section 2, the long-term consequences for innovation are explored. Section 3 deals with long-term impacts on trade. In section 4, the long-term implications for innovation

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and trade are evaluated through the perspective of the already worrying decline in innovation and science that characterized the world before the outbreak of COVID-19. Section 5 concludes that the world circa 2020 has a growing number of features in common with the medieval world, which has been further exposed by the COVID-19 pandemic. These include an increasing market concentration, dominance and defensive innovation by large superstar and zombie firms - reminiscent of medieval industrial Guilds and Feudal overlords; a return of Mercantilist notions to center stage as far as trade is concerned; and a rise in anti-science sentiment. The challenges for industrial policy under such sub-optimal Medieval-like conditions are discussed.

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## 2 New Industrial Guilds?

If we consider previous crises, such as the 2008-2010 global financial crisis, or the 1930s Great Depression, we see long-lasting impacts on innovation and related measures such as entrepreneurship (Shiller, 2020). For instance, evidence indicates the Great Depression harmed technological entrepreneurship and innovation in the USA for more than seventy years (Babina et al., 2020). And entrepreneurship in the USA, as measured, for instance, in the annual number of startups or the establishment opening rate, has not yet recovered to pre-2009 levels following the global financial crisis (Naudé, 2020b).

There are several reasons to be concerned that the COVID-19 crisis will, indeed, as previous crises, be followed by long-lasting reductions in innovation. One mechanism is through increasing inequality. Previous pandemics have been associated with rising inequality (Furceri et al., 2020), and that this is also likely to be the case with COVID-19. For example, Palomino et al. (2020) expect income inequality in European countries to rise by between 2 and 21 percent. This is bad news for innovation because inequality, after certain levels, tends to reduce innovation (Doucouliagos, 2017).

Another mechanism through which the COVID-19 crisis can cause a reduction in innovation is through further increasing market concentration and "superstar" firm dominance, as well as having as an unintended side-effect the prolongation of so-called "zombie firms" (McGowan et al., 2017). Even before the pandemic broke out, a growing literature documented the decline in innovation associated with superstar market-dominance and zombie firms, including through "defensive" innovation (Akcigit & Ates, 2019; Dinopoulos & Syropoulos, 2007; Song et al., 2015).

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The COVID-19 pandemic can deeper entrench market dominance through the further shift towards online trade and automation as accelerated by the pandemic (Bloom & Prettner, 2020), by rising government spending on bailouts (The Economist, 2020a,b), and the long-term impacts of the likely permanent reduction in startups (Fairlie, 2020; OECD, 2020; Sedláček & Sterk, 2020). As put by *The Economist* (The Economist, 2020a), the "splurge" by governments to rescue large corporations could lead over the long term to "a vast and lasting expansion of the state together with dramatically higher public debt is likely to lead to a lumbering, less dynamic kind of capitalism."

The fact is that the world is already experiencing a very undynamic form of capitalism, labeled as "platform capitalism" (Srnicek, 2016) as well as a stagnating type of capitalism, characterized by "declining business dynamism" (Decker et al., 2017). The growing list of scholars and authors diagnosing contemporary capitalism to be in - possibly terminal - crisis includes Collier (2018) and Milanovic (2020). To this list can be added growing concerns about the robustness and future of democracy, as *Freedom House*[1] warns that "a shift in the global order is challenging long-standing democracies.... With many citizens expressing doubts that democracy still serves their interests."

The high and rising levels of market concentration, declining new firm entry, defensive innovation, zombie firms, return of big government, and democracy in retreat can perhaps remind one of the conditions that pertained under industrial guilds and feudal overlords during the Middle Ages. It is worth recalling that after Germany's unification in the 1870s and subsequent industrial revolution, the reform of its system of industrial guilds was imperative, as it was standing in the way of adopting new industrial innovations[2] (Ogilvie, 1996, 2004).

## 3 A Return to Mercantilism?

As far as trade is concerned, the World Trade Organization (WTO)[3] has shown that the growth trend in world merchandise trends permanently slowed down after the 2009 global financial crisis - see Figure 1. Whether it will do so again after the COVID-19 pandemic is in my view still an open question, although Razin (2020) makes a good case that the COVID-

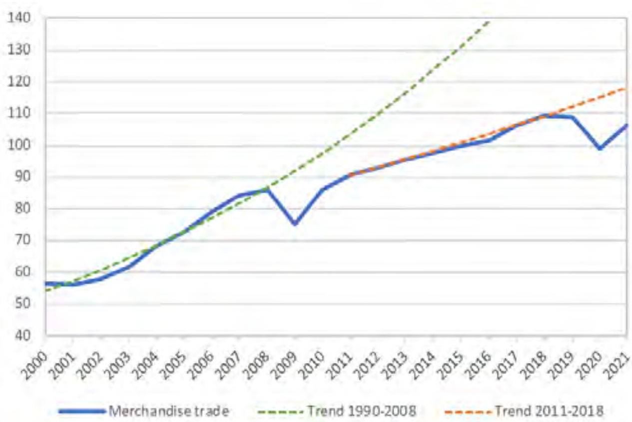
[1]See https://freedomhouse.org/report/freedom-world/2019/democracy-retreat.

[2]Ogilvie (1996, pp.286-287) describes how the guilds constrained innovation by reference to the case of how "the Remscheid scythe smith's guild successfully resisted the introduction of water-driven scythe hammers in the 18th century" – See also the discussion in Naudé & Nagler (2018).

[3]See https://www.wto.org/english/news_e/pres20_e/pr862_e.htm

19 pandemic will "add further momentum" to de-globalization that had already started a decade ago. How strong this further momentum will be, will partly depend on the nature of the contraction in global GDP. So, for instance, it seems that merchandise trade was less affected during the COVID-19 crisis than during the global financial crisis.[4] The WTO has pointed out that "the volume of world merchandise trade is only expected to decline around twice as much as world GDP at market exchange rates, rather than six times as much during the 2009 collapse." Indeed, according to the RWI/ISL Container-Throughput Index[5] , by July 2020, trade had recovered to before 2020 levels, and "cargo handling in Chinese ports again reached an all-time high" in July 2020.

Figure 1: *World Merchandise Trade, 2000 - 2021*




*Data source*: World Trade Organization, at https://www.wto.org/english/news_e/pres20_e/pr862_e.htm.

Trade has been, at least over the short-term so far, more resilient during COVID-19 than during the global financial crisis. A possible reason is that during the global financial crisis expenditure shifted away from tradeable to non-tradable and non-durable goods (Eaton et al., 2016). In contrast, during the 2020 COVID-19 crisis, there has not been a similar relative shift in expenditures towards services, because services sectors, including travel, tourism, and hospitality services, were effectively locked down, whereas, in contrast, production and distribution of physical goods could continue with relatively fewer restrictions, given that they require less face-to-face interaction (Avdiu & Nayyar, 2020).

[4]The glaring difference in trade in medical supplies: more than 90 countries restricted exports of medical supplies such as personal protective equipment (PPE), ventilators and respirators amongst others (Desta, 2020).

[5]See https://www.isl.org/en/containerindex

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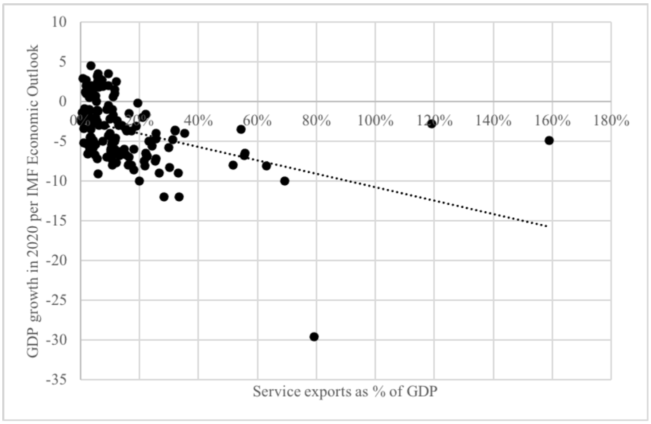
Thus, during COVID-19, we have seen a relative expenditure shift towards tradeable, manufactured goods away from services, thus benefiting countries and regions with manufacturing industries more. Preliminary data available tend to support this, in those countries where services trade was more critical suffered significantly more in terms of GDP contractions – see Figure 2.

Figure 2: *Countries more dependent on Service Exports tend to suffer more significant declines in GDP growth*




*Data source*: Author's calculations based on data from the World Bank Development Indicators online and the IMF World Economic Outlook, April 2020.

Hence countries with more substantial manufacturing sectors and other goods-producing sectors such as agriculture and mining were thus more resilient during the pandemic. This experience is likely to reinforce the well-founded notion that what a country produces and exports matters and that diversification of production and trade is welfare-enhancing and protect against external shocks and volatility (Cadot et al., 2013; Hidalgo et al., 2007).

With industrialization, in particular manufacturing, still mattering and indeed having been showed to be essential for volatility reduction and resilience during the COVID-19 pandemic, one should be gravely concerned for the anti-trade (and anti-globalization) backlash that has become evident in recent years (Macgregor-Bowles & Bowles, 2017; Dür et al., 2020; Razin, 2020). In particular, just as COVID-19 illustrated the importance of open trade, the ability of countries to industrialize through trade is being thwarted by the rise of economic nationalism (Born et al., 2019) and the increased marginalization of the WTO (Bagwell et al., 2016). In the latter regard, Jean (2020, p.137) refers to the violation of the WTO's Agreement on Subsidies and Countervailing Measures (SCM) by many countries in an attempt to support

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their domestic industries during the crisis and concludes pessimistically that "the pandemic and the ensuing structural changes can only add to the feeling that WTO rules have been conceived in a context that differs substantially from the one we are living in, increasing the risk of a loss of legitimacy. The rules-based trading system is threatened with irrelevance, and the inability of the WTO to play an active role in coordinating responses since the outbreak of the crisis does not help to assuage these concerns."

Economic nationalism and the jettisoning of the rule-based trading system, all fueled by anti-globalization sentiment, is sending the world back into what could perhaps be described as a return to Mercantilism (Barro, 2019). It is reflected in China's neo-Mercantilism (Yu, 2019), the growing popularity of the so-called "Beijing Consensus" amongst developing countries (Halper, 2010), the USA-China trade war[6] (Chong & Li, 2019), and even the Brexit (Born et al., 2019). If not precisely medieval, we are experiencing a distinctly 19th-century approach[7] to trade and geopolitical rivalry (Dent, 2020).

This Mercantilism will not only be detrimental for industrialization by restricting the benefits of trade but ultimately damaging for global health outcomes and the ability of the world to respond to current and future pandemics. Macgregor-Bowles & Bowles (2017) note at least four pathways through which Mercantilism and the rise of anti-globalization could lead to a deterioration in global health, namely through promoting protectionism, increasing xenophobia, rising military spending (which crowds out aid and health budgets), and by exacerbating climate change. Besides, Mercantilism tends to spill over into other terrains – including health. During the COVID-19 pandemic, the mercantilist-inspired USA-China trade war concretely spilled over into the health sphere, as reflected in the politicization of the WHO, which caused Fidler (2020) to warn that "The manner in which China and the United States politicized COVID-19 for geopolitical purposes bodes ill for international health cooperation."

[6]With reference to the USA-China trade war US President Trump has notoriously stated on Twitter that "Trade wars are good, and easy to win." They are neither. See https://www.theatlantic.com/ideas/archive/2019/08/trade-wars-are-not-good-or-easy-win/595546/

[7]Or, as Rampell (2018) writes in the Washington Post "Trump's trade policy is stuck in the '80s - the 1680s." As the above paragraphs makes clear with reference to China's neo-Mercantilism, the Beijing Consensus and the Brexit, it is not only in the USA where regressive trade policies are holding sway.

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## 4 Is the 4IR Facing a Premature Demise?

That the world is increasingly characterized by conditions which remind of previous centuries, such as the rise of new "Guilds" and neo-Mercantilism, is accentuated by the fact that even before the COVID-pandemic broke out, the world was being characterized by stagnating innovation and a rising anti-science sentiment. This significantly weakens the prospects of industrialization, particularly so as this pre-existing condition may be exacerbated by the COVID-19 pandemic - as the previous two sections argued. In this section, I will consider in more detail the pre-existing condition of stagnating innovation and anti-science sentiment, to try and understand whether industrialization may be viable after the pandemic, and if so, what this means for the so-called 4th Industrial Revolution (4IR).

That the world was suffering from stagnating innovation before catching the COVID-19 pandemic is perhaps surprising to some, but generally uncontroversial. Gordon (2012, 2016) and Cowen (2010, 2016, 2017) contains essential expositions of the "Great Stagnation" and Ridley (2020) describes the extent and reasons of the "innovation famine". Naudé & Nagler (2018) document the long-term decline in Germany's innovation, showing its current industrial structure and big corporations were inherited mainly from its very innovative late-19th century.

Bloom et al. (2020) ascribe the decline in innovation to the possibility that "ideas are getting harder to find" concluding that the USA must double its research effort every 13 years to counter the effect of ideas getting harder to find. Erixon & Weigl (2016, pp.10-11) ascribes the decline in innovation instead to defensive corporate strategies, which is reflected in a lack of corporate renewal, pointing out that "In Germany's DAX 30 index of leading companies, only two were founded after the 1970s. In France's CAC 40 index there is only one. In Sweden, the 50 biggest companies were created before the start of World War I in 1914 and the remaining 20 were founded prior to 1970. If you compile a list of Europe's 100 most valuable companies, none were actually created in the past 40 years."

In section 2 the consequences of defensive innovation by market-dominating superstar and zombie firms were described. It was argued that the COVID-19 pandemic might consolidate and even strengthen the market power of incumbent firms and depress further the entry of new firms, thereby further undermining the potential for corporate renewal. Moreover, large incumbent firms will be even more likely not only to engage in defensive innovations such as creating patent thickets or buying up new ventures but moreover utilize these expressly to limit the diffusion and spread of new knowledge (how innovation and trade historically

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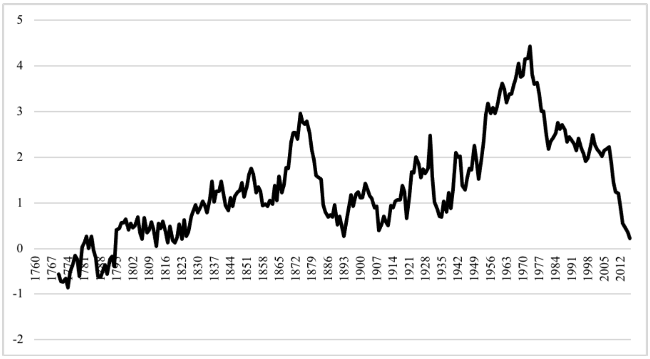
contributed to industrialization) – which will further make new ideas harder to find. After all, as Akcigit & Ates (2019, p.3) "when knowledge diffusion slows down, market leaders are shielded from being copied, which helps establish stronger market power."

Innovation, an engine of industrialization, is therefore becoming less and less effective in fulfilling this role. Whereas the 1st and 2nd Industrial Revolutions were characterized by large gains in labor productivity growth and subsequent wage increases, labor productivity growth in the West has stagnated since the 1970s and decoupled from wage growth (Brynjolfsson & McAfee, 2016). The decline in labor productivity growth since the 1970s has been notable in many Western economies – see Gordon (2018). It is perhaps most dramatically seen that labor productivity growth in Great Britain has declined by 2016 to its lowest rate in more than 200 years – see Figure 3.

Figure 3: *Labor Productivity Growth (GDP per hour worked) in Great Britain, 1770-2016 (10-year moving average)*




*Data source*: Author's calculations based on A Millennium of Macroeconomic Data by the Bank of England, available at `https://www.bankofengland.co.uk/statistics/research-datasets`.

As a result of the declining labor productivity growth rate, potential GDP growth has declined in affected economies, for instance, from 2,1 percent in 1998 to 1,0 percent in 2015 in the OECD (McGowan et al., 2017). There is another implication of the decline in innovation and labor productivity that is relevant to the discussion on industrialization post-COVID-19. That is that the so-called 4th Industrial Revolution (4IR), which has, in recent years become a leitmotiv in virtually all countries' industrial policies, may after the pandemic face a premature demise. There are several reasons for this, which I will discuss in the remainder of this section.

First, mention has already been made that all previous real industrial revolutions were

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accompanied by rising labor productivity growth. The 4IR is conspicuous by the absence of wide-spread labor productivity growth and the absence of mass technological unemployment, as was expected by some (Gries & Naudé, 2020). There are of course some firms - the minority - that benefit in terms of productivity from 4IR technologies, but as Andrews et al. (2016) note, the laggards are far more prevalent. It could of course also be the case that there are implementation lags and that the productivity gains are still in the future (Brynjolfsson et al., 2017) - see for instance the example in Juhász et al. (2020) of the diffusion of mechanized cotton spinning in France during the 1st Industrial Revolution. The problem is, that if this is the case for 4IR technologies, then the COVID-19 pandemic, and the declining innovation, rising concentration and de-globalization that it is accompanied with, will only serve to further delay the diffusion of technologies.

Second, many of the critical technologies espoused as 4IR technologies, such as Artificial Intelligence (AI), advanced computing, connectivity (the Internet of Things), 3D-printing, and renewable energies, have not (yet) lived up to their promise. To start with, consider that innovation in renewable energy has been characterised by a decline in patenting, start-ups and venture capital since around 2010 and that still less than a fifth of US electricity is generated by renewables (Popp et al., 2020). Globally only 11% of primary energy needs are met by renewable energies.[8] And 3D-printing (additive manufacturing), a technology from the 1980s, has so far failed to ignite a global revolution in localized small-scale niche manufacturing, remaining essentially restricted to create (very usefully) molds and models (Tserovski et al., 2019). As Kleer & Piller (2019, p.23) recently pointed out "Wide adoption of this technology is predicted but not yet achieved" - they refer to a Delphi study on the future of additive manufacturing finding " large uncertainties and little consensus among the participating experts."

Perhaps one of the most hyped technologies of the 4IR is AI. Thus, it is notable that AI has been of relatively little value in fighting the pandemic (Naudé, 2020a). Instead, as Rotman (2020) remarked, "our most effective response to the outbreak has been mass quarantines, a public health technique borrowed from the Middle Ages." Moreover, instead of revolutionizing manufacturing as some are touting[9] AI to do, AI is not diffusing fast, nor is its technical potential yet attained. AI remains expensive, mostly out of reach of small businesses, who do not have access to large enough data-sets to train AI models, as well as not safe enough, and increasingly burdened in its implementation by (expensive) regulations (Naudé, 2019; Far-

[8] From Our World in Data: `https://ourworldindata.org/renewable-energy`

[9] See for instance this article in MIT Technology Review : `https://www.technologyreview.com/2020/09/29/1008933/how-ai-will-revolutionize-manufacturing/`

boodi et al., 2019). Moreover, whereas many had pinned their hope on the 4IR to promote green industrialization, it is increasingly evident that AI, at least in its current form based on Machine Learning (ML), comes at a substantial environmental cost. Schwartz et al. (2019) report that "Training a large, deep-learning model can generate the same carbon footprint as the lifetime of five American cars, including gas."

Like AI remaining limited in adding real value to manufacturing on a broad and sustainable scale, so too do we yet have to see the potential of the Internet of Things (IoT), 3D-printing (a 1980s technology), and renewable energy to be realized. In their book *The Internet of Things Myth*, Hatton & Webb (2020) make the point that "Unlike the home environment where Wi-Fi is universal, there is no standard for connecting distributed IoT devices. There have been a number of pretenders to the throne, but no single technology has yet emerged around which the whole IoT ecosystem can converge. Neither does there seem to be a single viable candidate, despite what the proponents of 5G might claim." And despite digital technologies, our transportation systems are hardly significantly better than the 1950s. Preston & Waterson (2015) remark that "Railways were being rolled out rapidly from the 1830s, while the commercial breakthroughs in petrol and diesel engines date to 1876 and 1892 respectively. Even the jet engine that made mass aviation possible can be traced back to Frank Whittle's first patent in 1932 [...] Despite decades of futuristic predictions, modern transport wouldn't look all that different to someone from the 1950s". Given the lack of fundamental progress in transportation, it remains the case, very much as in earlier ages, that "trade logistics are the most important non-tariff factor in predicting international trade" (Abrego et al., 2019).

Despite the promise of the 4IR, productivity growth in the advanced economies shows no sign of revolutionary change, as it did in all of the previous industrial revolutions. Moreover, one could very plausibly argue that the technologies associated with the 4IR, such as connectivity and mobile computing, enabled the rise of social media with its downsides, including violations of data privacy, which has now led to a tech backlash (Hendrickson & Galston, 2019; Feldstein, 2019). We read more in the news about voter manipulation, fake news, growing cybercrime, and the pernicious effects on society of echo chambers, filter bubbles (like Medieval walled castles), and exploitation on online labor platforms, as well as of the regulatory battles of governments against digital platform giants, than of improved productivity or rising wages and new, sustainable manufacturing processes spreading (Chen, 2019; Coyle, 2017; Moore & Tambini, 2018). The COVID-19 pandemic has brought to the fore concerns about digital technologies being misused for disinformation and misinforma-

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tion[10] (Brennen et al., 2020; Naudé & Vinuesa, 2020) and strengthening the surveillance state (Harari, 2020).

A third reason why the 4IR may suffer a premature demise is that on top of the increasing doubts about the impact of 4IR technologies, and the recognition of the downsides of these technologies, the world is taking a worrying anti-science turn (Dawkins, 2017; Levine, 2017). Hotez (2020) describes the rise of anti-science movements in the USA in climate change, air pollution, and biomedical sciences, including vaccines. Saad (2020) considers the rise of anti-science as partly the result of several "idea pathogens" under which he includes postmodernism, radical feminism, and transgender activism. These idea pathogens and the anti-science beliefs they result in are often somewhat ironically fostered and nurtured on university campuses.[11]

Erixon & Weigl (2016) expressed concern that innovation and entrepreneurship are being further strangled by the anti-science culture emerging in many universities where science is increasingly taking a second place in favor of precautionary, risk-avoidance behavior in the extreme. This stifles free speech, essential for progress in science and innovation. In their words (p.38) "There are ever-growing demands for 'safe spaces' where students would be allowed to shield themselves from academic teaching and thinking they do not like." Such safe spaces are not necessarily inspired only by risk aversion or excessive precaution-taking, but also, as Goldberg (2018, p.218) points out, "as an effort to control certain battles spaces in the culture war." It would thus seem that also in our beliefs and sense-making systems, that the current age is exhibiting Medieval characteristics, where idea pathogens and culture wars combine to restrict the flow of scientific knowledge and spread dis-and misinformation.

This anti-science turn is of concern for industrialization post-COVID-19, not only in that it limits free speech and the flow of knowledge and the freedom to experiment and dissent, essential for innovation, but that it takes place when progress in, and funding of, science is under pressure. Weinstein (2012) has expressed concern that in fundamental physics, the field responsible for virtually all of the technologies underpinning earlier industrial revolutions, from the steam engine to electricity, electronics, and nuclear power, has been stagnating since the 1970s. And Funk (2019) has noted the decline in venture capital funding going into

[10] To try and counter some of the misinformation and disinformation being spread about the pandemic, the Infodemic Observatory evaluates around 4.7 million 'tweets' per day on for their reliability - see `https://tinyurl.com/y5bfush6`.

[11] Consider, as an example, the following statement that was made at a "de-platforming" protest on a US university campus, as reported by Sullivan (2018) "Science has always been used to legitimize racism, sexism, classism, transphobia, ableism, and homophobia, all veiled as rational and fact, and supported by the government and state. In this world today, there is little that is true 'fact'."

non-digital science-based technologies such as semiconductors, fiber optic communications, mobile communications, and medical instruments. For instance, and very pertinently in light of the COVID-19 pandemic, venture capital funding going into medical instrument technologies declined by over 50% between 2003 and 2017.

The causes of anti-science sentiment, stalled progress in fundamental physicals, and declining investment in (non-digital) science-based technologies are myriad and complex; however it is likely that the over-regulation of these areas, and the growing amount of "permissions" that need to be obtained to be innovative in various scientific fields and bring these innovations to markets, (as opposed to digital services) are playing a contributing role (Erixon & Weigl, 2016; Thierer, 2016). Fixing the engine of innovation for industrialization post-COVID-19 may require a more "permissionless" and permissive environment for entrepreneurial innovation, as well as better understanding "crisis innovation," as Gross & Sampat (2020) argues with reference to the Second World War.

# 5 Concluding Remarks

Industrialization, in particular through the manufacturing sector, remains a vital economic transformation trajectory for inclusive and sustainable global development. The two engines of industrialization – innovation and trade – are in danger of being (further) compromised by the COVID-19 pandemic.

Moreover, innovation and trade are being compromised at a time when both innovation and trade had already been under pressure. Innovation had been stagnating due to, amongst others, the evolution of global capitalism, that had seen the rise of platform capitalism and concentration in and dominance of markets by large superstar firms and zombie firms, many of them aged, and engaging in defensive innovation - in a manner reminiscent of the medieval guilds and feudal overlords. Trade had been under pressure due to rising economic nationalism and trade wars, with the rules-based multilateral trading system losing credibility – signaling an increasing application of mercantilist views and ushering in a period of de-globalization.

The COVID-19 pandemic may cause a long-term reduction in innovation and entrepreneurship, as section 2 of this paper argued. This will delay and even bring to a premature end the 4th Industrial Revolution (4IR). The technologies of the 4IR were of limited help against the pandemic so far - apart from allowing some to work remotely and to share information

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fast.[12] Hence, doubts are arising as to whether the promises of and expectations of other key 4IR technologies, such as the IoT or 3D-printing and renewable energy and advances in transport, would ever materialize, at least to the extent that it would meaningfully impact on manufacturing.

So far, as the world economy recovers from the pandemic, it is evident that the 4IR has been the only industrial revolution that has been accompanied by a stagnation in general labor productivity. As was shown as an example in section 4 of this paper, labor productivity growth in the UK was in 2016 at its lowest level in 200 years. Of even more concern, not only did the technologies of the 4IR not help so much against COVID-19 or to drive labor productivity and potential GDP growth, but these technologies have also contributed to creating new problems such as surveillance states, disinformation, and misinformation about the pandemic, rising cybercrime, amongst others. More than ever, Peter Thiel's comment that "we wanted flying cars instead we got 140 characters" reflects the disappointment of an age that expected sustainable global development from a new industrial revolution driven by "brilliant" technologies and open and fair trade. It appears that instead of a 4th industrial revolution, we got to wear masks and raise the proverbial bridges across our moats. With innovation and trade, the engines of industrialization, in jeopardy, what are the options?

It would seem, at least over the foreseeable future, that sub-optimal policy-making will be the inevitable resort of governments and multilateral agencies. The question may be, what is easiest to fix: innovation or trade? If only one can be fixed, at least industrialization may be able to fly on one engine. For example, if the stagnation in innovation is too complicated to solve soon given the dominance of the new industrial "guilds" and challenges in physics, then the second-best option may be to assure that existing technologies and know-how at least flow with increasing speed throughout the world to allow for convergence. This would require trade openness and globalization to be furthered, not retarded. And *vice versa*, in a mercantilist world, with trade disabled as an engine of industrialization, the second-best may be to nurture innovation and entrepreneurship, which will require the opening up of domestic economies to competition and new entrepreneurs, and the promotion of permissionless innovation.

In my view, it is perhaps too difficult to fix the innovation system in time. We do need the technologies of the 4IR and do need the 4IR to turn out more than a promise; however, fixing the regulatory, funding, scientific and entrepreneurial constraints on innovation will run into

[12] See also the analyses on the limited contribution made by smartphone contact-tracing apps against the pandemic by Barber & Knight (2020) and the editorial in *Nature Biotechnology* at `https://doi.org/10.1038/s41587-020-0610-4`.

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formidable obstacles. Following COVID-19, decision-makers may retreat into a safer, less risky, and less uncertain world than the current. The aging demographic in much of the advanced economies are likely to give this further impetus.

This will leave trade as the only engine for industrialization in the near future. Fortunately, the rules-based multilateral trading system is not yet irredeemably damaged despite deglobalization and the return of Mercantilism. There is still a (very) small possibility that the global trade system may be reformed, even if in a direction that will better help developing countries to raise their welfare through industrialization based on imitation, rather than innovation. If the world fails to get trade fixed, it will likely also start to resemble the Middle Ages in other, even worse, aspects.

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# The reallocation effects of COVID-19: Evidence from venture capital investments around the world[1]

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

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1 The scientific output expressed does not imply a policy position of the European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use which might be made of this publication.

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## 1. Introduction

The outbreak of the COVID-19 pandemic and the resultant social distancing measures that restricted business activity and movement of people caused a sudden and unprecedented stop to economic activity and a globally synchronized contraction in GDP (IMF, 2020). According to the World Economic Outlook released by the International Monetary Fund in June 2020, the annualized growth of global real GDP was projected at -4.9%, compared to a +3.3% projection released in January 2020 just before the global spread of the pandemic. In advanced economies, the contraction was even larger.[1] It is widely believed, however, that the economic effects of the pandemic would not be restricted to a severe recessionary twin supply-demand shock but would also trigger broad reallocations of real and financial resources across sectors and firms (Barrero et al., 2020; OECD, 2020).

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

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

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

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

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and Strömberg, 2004; Gompers et al., 2008; Gompers et al., 2020a). Thus, it is not surprising that many analysts and commentators claimed at the time that "while traditional VC investment is expected to slow significantly over the next quarter, there are several niche segments of the market that could remain attractive to investors due to their applicability in the current environment" (KPMG, 2020).[2] Or, as argued by a study of EuropeanStartups.co,[3] while one third of the European VC-backed companies are strongly vulnerable to the pandemic crisis, for 20% of European tech-companies it represents a net benefit and an opportunity.

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

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

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

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

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

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

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

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operationalization of treatment. We also show that investments in deals related to social distancing also increase in the aftermath of the spread of COVID-19.

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

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

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

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

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

## 2. Data and empirical strategy

### *2.1. Data structure and sources*

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

To this end, we start with all VC deals that took place between January 2018 and July 2020 in 126 countries around the world available on Zephyr, a Bureau van Dijk database.[4] The database provides information on 1) characteristics of VC deals, such as invested amount, transaction date, and deal description; 2) VC investors, such as name and place of origin; and 3) companies raising capital, such as name, place of origin, and industry. The main advantage of the database is that it includes a deal synopsis. The synopsis can be used to identify deals involving ventures that develop technologies suited to tackle the needs of businesses and consumers in an environment of health pandemic and social-distancing (hereafter, we call such deals "pandemic-related"). To capture the spread of the virus by country, we obtain data from a public database "Daily confirmed COVID-19 cases", produced and updated by European Centre for Disease Prevention and Control (ECDC) and hosted by Our World in Data – a public data repository developed by the University of Oxford.[5] The database provides information on the diffusion of the disease by country, including the date of the first detected case of COVID-19.

[4] Using this time span, we can address the seasonality and cyclicality in VC investment by comparing any given post-COVID period to two pre-COVID periods during the previous two years. For instance, we can compare VC investment during March 2020 to that of March 2019 and March 2018. Given the cyclical nature of VC investment suggested by Cox et al. (2017) and Gompers et al. (2008), this approach should reduce possible biases that might arise through a comparison of pre- and post-COVID-19 periods.

[5] The database is available at https://ourworldindata.org/grapher/daily-cases-covid-19.

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Our empirical strategy, discussed in detail in the next sub-section, follows a difference-in-differences approach. We compare VC investment flows in deals that involve ventures developing technologies related to the mitigation of contagious diseases like COVID-19 and social distancing problems to flows in deals unrelated to a pandemic environment, before and after the onset of the COVID-19 crisis. This requires the organization of the data in a panel structure with time-series and cross-sectional dimensions. As a temporal unit, we adopt 2-week periods, for a total of 62 bi-monthly periods. Our rationale is as follows: On the one hand, adopting a daily or even weekly frequency might lead to insufficient number of deals within a temporal unit and a few large deals could influence our results. On the other hand, we want to ensure that our treatment time-point is well defined. Adopting a monthly frequency would treat deals completed 30 days apart as part of the same temporal unit, which might not be appropriate given the speed of COVID-19 diffusion.[6]

For the cross-sectional dimension, we follow two approaches. First, at the global level, we aggregate all VC deals into two categories – pandemic-related and non-pandemic – for each of the 62 bi-monthly temporal units. We discuss these categories in detail in the next sub-section. Thus, in this "global dataset" we have two observations per temporal unit for a total of 124. This allows us to study the reallocation effects of COVID-19 under the assumption that VCs respond to a global signal for the outbreak of the pandemic. Our second approach focuses on the country level as the cross-sectional unit and we construct a "country dataset". For each of the 126 countries in our database, we aggregate all deals for the 62 temporal units into two deal categories (pandemic-related and non-pandemic). This results in a total of 15,624 observations reflecting all possible time period-country-deal category combinations.[7] This dataset allows us to incorporate the staggered nature of the spread of COVID-19 across countries and implement a staggered DiD approach.

### *2.2. Treatment*

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

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

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In our main analysis, we categorize as pandemic-related deals that are strictly associated with the health value-chain and in the fields of biology, chemistry, healthcare, and pharmaceutical development. To determine if a deal should be assigned to the pandemic-related category, we use an "Information Extraction from Text" method (Jiang, 2012). The method analyzes unstructured text to collect information and provide structured informative output. Following this approach, we analyze 3 textual fields of the sample deals, namely: deal editorial, comments, and rationale. Deal editorial and comments are provided by Zephyr analysts and describe the main features of the deal, including information about target firm and its projects (Reiter, 2013). Deal rationale is generally sourced from press releases or communication produced by the firm (Florio et al., 2018). We assign a deal to the pandemic-related category if at least one of the textual fields mentions at least one word from a list of predetermined keywords. The list consists of 5 groups of words related to "biology", "chemistry and pharmaceuticals", "health", "healthcare supply chain", and "medical science".[8] We create a dummy variable, *Pandemic*, which takes the value of 1 if the deal textual fields mention at least one key word, and 0 otherwise. To not undermine our DiD strategy, we use words that can be found in the deal synopses even before the novel coronavirus was isolated by the Chinese Centre for Disease Control and Prevention in January 2020 under the provisional name 2019-nCoV. Therefore, we exclude words commonly used to designate the current pandemic, such as novel or new coronavirus, 2019-nCoV, COVID, COVID-19, SARS, and SARS-CoV-2.

An alternative approach to identify pandemic-related deals might be to classify sectors as pandemic-related based on technological characteristics that make them more sensitive to a health pandemic (or social distancing), and then use the sector of a target firm – usually identified through NACE codes[9] – to establish if a deal is pandemic-related.[10] However, in our context this way of

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

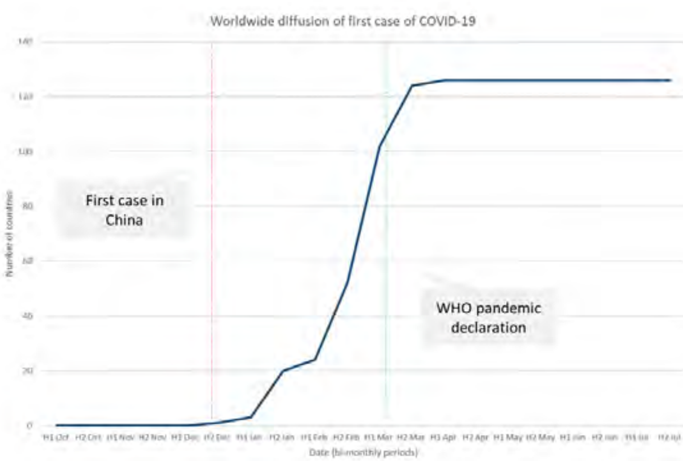
[9] European Commission (2008). NACE Rev. 2. Statistical classification of economic activities in the European Community. *Eurostat Methodologies and Working Papers*, Office for Official Publications of European Communities, ISBN 978-92-79-04741-1, https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

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

categorizing a sector based on the average characteristics of firms belonging to it does not take into account intra-sector heterogeneity of entrepreneurial ventures and can lead to measurement errors. On the one hand, projects related to a health pandemic may be developed by firms operating in sectors other than healthcare. On the other, some projects launched by firms in the healthcare sector might clearly be non-pandemic.[11]

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

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




The first confirmed case emerged in China on December 31, 2019, even though according to the media, Chinese authorities had identified cases of the virus weeks earlier.[12] In the following

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

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

months, by mid-March 2020 when WHO officially declared pandemic status, most of the countries around the world (about 80%) had faced the disease.[13] For the remaining 20%, the first COVID-19 case emerged during the first two weeks of April 2020. The time-series pattern suggests that while the diffusion of COVID-19 was relatively quick, there is a degree of variability in its spread across countries. Hence, given that our temporal unit of analysis is a 2-week period, we construct a dummy variable, *First Case G*(lobal), which takes the value of 1 for deals occurring after the second half of December 2019, and 0 otherwise. While this approach captures the earliest signal for the (potentially) global pandemic, it is possible that VC investors could not fully anticipate the magnitude of the upcoming crisis. As a result, we might underestimate reallocation effects. Hence, we construct another dummy variable, *WHO*, which takes the value of 1 for deals occurring after the second half of March 2020 when the WHO declared a global pandemic status. We note that, as mentioned, by that time most countries have already experienced COVID-19 cases. Therefore, to implement our preferred empirical approach at the country level, we construct a dummy variable *First Case C*(ountry), which takes the value of 1 for deals funded after the 2-weeks period in which the first COVID-19 case for the specific country was confirmed.

### *2.3. Dependent variables*

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

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

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

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and time-series patterns to those reported in Pitchbook.[14] This suggests that our analysis is based on a representative sample with comprehensive worldwide coverage. Similarly, Figure A.3 shows the average bi-monthly number of VC transactions over periods before and after the pandemic onset for the world market, as well as the US, China, and the European Union. We note that US figures follow a similar path to the one reported by Howell et al. (2020) based on CB Insights data.

### *2.4. Econometric strategy*

To identify the reallocation effects on VC investment created by the spread of COVID-19, we rely on variations of a difference-in-differences methodology. The approach is extensively used in evaluation studies to examine whether an exogenous event (*Treatment*) has a causal effect on a given outcome of interest. In particular, the method compares changes in the outcome for a group of units subject to the event (*Treated*) and another group of units similar in all aspects except for not being subject to the event (*Control*), for a period of time before and after the event. In our context, we compare VC investments in pandemic-related (*Treated*) and non-pandemic (*Control*) categories before and after the onset of the spread of COVID-19.[15]

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

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

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

[14] See https://assets.kpmg/content/dam/kpmg/xx/pdf/2020/07/venture-pulse-q2-2020-global.pdf.
[15] Table A.3 in the Appendix reports t-tests of the differences in the means of the outcome variables for pandemic-related and non-pandemic deals.

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

Our second set of analysis explores the staggered spread of the COVID-19 pandemic across countries.[16] In this case, the model is specified as follows:

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

where *i* denotes a country and *t* and *d* denote time period and deal category, respectively. *First Case C* has a staggered nature and controls for common shocks to all deals in a given country after the spread of COVID-19 in that country. We control for unobserved heterogeneity across the units of analysis by including country-deal category fixed effect, $\mu_{di}$, along with time fixed effects to account for common shocks at time *t*, $\tau_t$. We also account for possible country-deal category trends through ($Trend_{dit}$) and cluster the errors, $\epsilon_{dit}$, at the country level.[17]

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

### *2.5. Preliminary evidence*

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

[16] Similar DiD estimation in country-by-sector setting is often used in research on financial and economic development (e.g., Braun and Larrain, 2005; Levchenko et al., 2009; Desbordes and Wei, 2017; Beck et al., 2018).
[17] We have also estimated equation (2) using standard errors clustered at the country deal-category level. The estimates are reported in Table A.4 of the Appendix. We note that our results are robust to this alternative approach.

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**Table 1 Evolution of VC Investments**

**Panel A Total Amount**

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

**Panel B Number of Deals**

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

**Panel C Median Amount**

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

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

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

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

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

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

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## 3. Results

### *3.1. Global analysis*

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

**Table 2 Global Flows of VC Investment**

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

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

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

### *3.2. Country-level analysis*

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

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

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

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

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

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

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

### *3.3. Heterogeneous effects*

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

*Geographic area*

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

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

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

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

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**Table 4 Heterogeneous Effects**

**Panel A Geography**

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

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

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

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

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

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

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

*Investor experience*

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

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

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

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

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

*Investment round*

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

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

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

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

*Type of investor*

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

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

## 4. Robustness tests

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

### *4.1. Common trend assumption*

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

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

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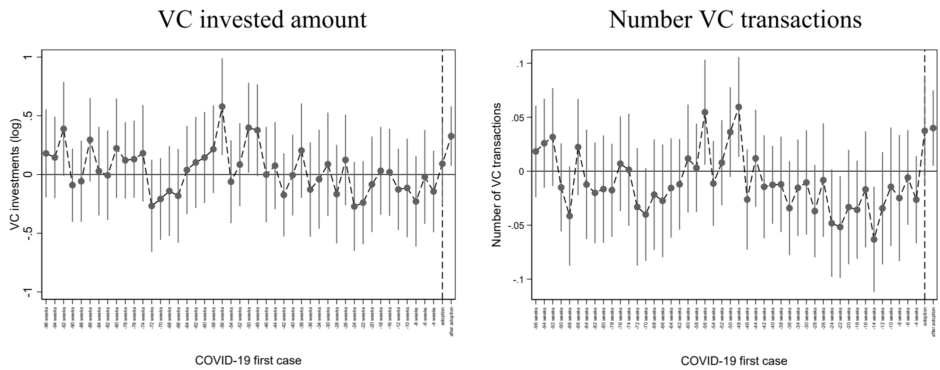
The coefficients $\alpha_t$ on the pre-treatment periods, with $t$ going from 48 bi-monthly periods to 2 bi-monthly periods before the first case of COVID-19 in country $i$, allow us to explore the possibility of non-parallel trends prior to outbreak. By contrast, the coefficient $\gamma_t$ shows the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

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




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

## *4.2. Other robustness tests*

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

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

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

## 5. Conclusions

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

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

We also document several heterogenous effects underneath the average estimates, namely, that the magnitude of the reallocation effect could depend on the experience and origin of the VCs,

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as well as investment stage of the transaction. Thus, our analysis highlights the role of the global pandemic for the functioning of the VC market.

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**Appendix**

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

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

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

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

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

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

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

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

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

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

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

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

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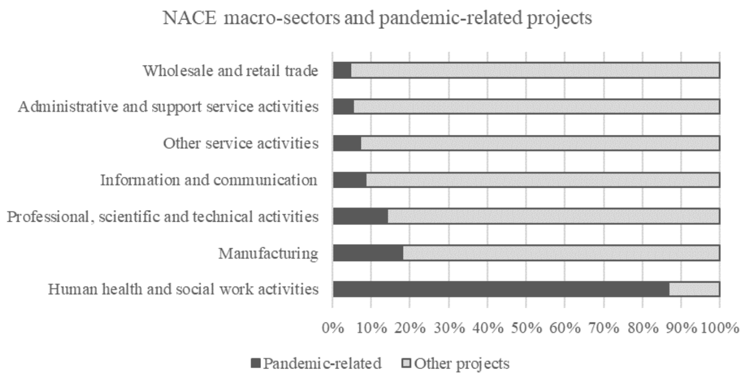
**Figure A.1 Distribution of Pandemic-related Deals across Main NACE Macro-sectors**




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

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

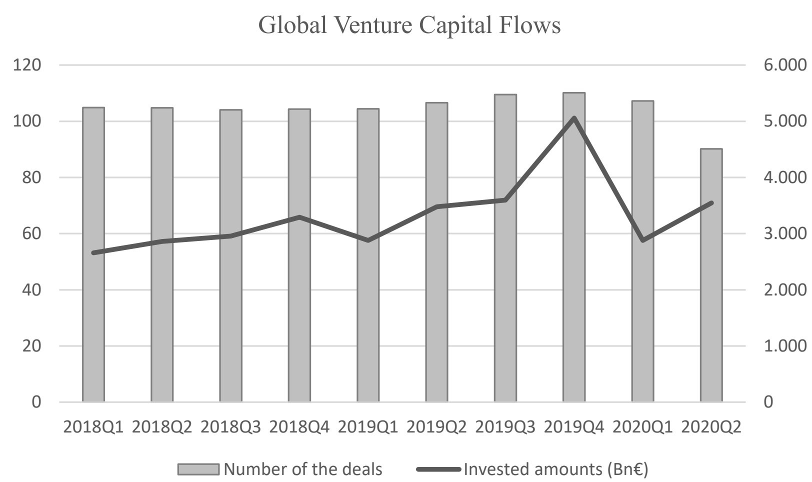



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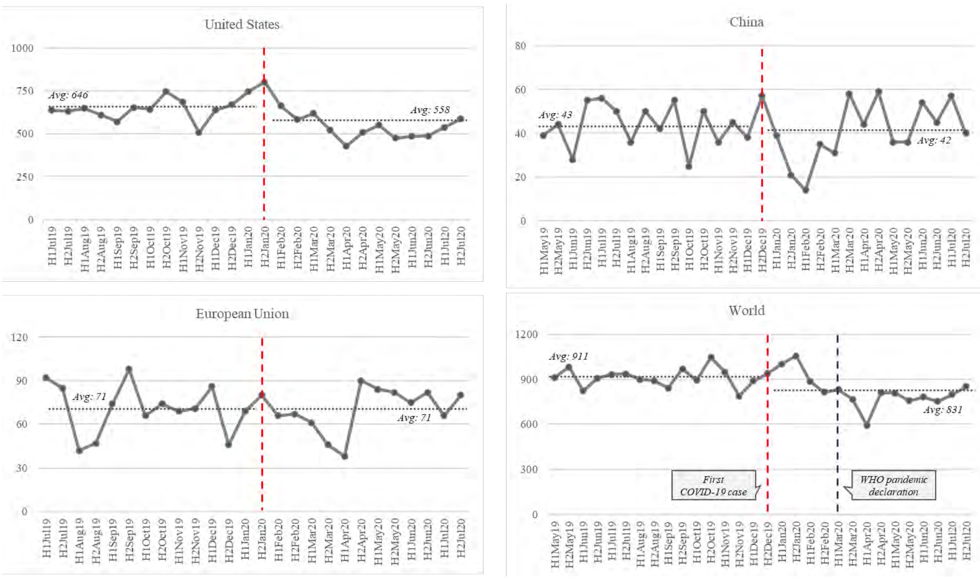
**Figure A.3 Evolution of VC Financing (before and since the pandemic)**




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